International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-8 Issue-4, November 2019

Retinex Color Balanced Piecewise Contrast and Fuzzy Trilateral Filter for Underwater Image Enhancement

A.Parameswari, M.V.Srinath

Abstract: *Over the past few years, underwater observation has become an active research area. Due to the higher rate of image degradation in the underwater environment, image enhancement has become one of the problems to be addressed for the underwater research. Underwater images face limitations like color correction, white balance, color contrast and haze. To overcome those problems, a novel fusion method based on the Retinex Color-balanced Piecewise-contrast and Fuzzy Reinforced Trilateral Filter (RCP-FRTF) method is presented for underwater image improvement. With the underwater image given as input, to start with, a color correction model based on the Retinex multi proportions is presented. With the color corrected output obtained, an Eigen-based White Balancing method is applied to generate color balanced model. With the color balanced underwater image, color contrasting is performed using the Piecewise Linear Color Contrast model. After obtaining the latter, the contrast is said to be improved to a better level. Finally, to generate a haze-free image a Fuzzy Reinforced Trilateral filter is applied. The enhanced and de-hazed images are distinguished by reduced noise level, thus enhanced visibility and contrast while the finest edges are enhanced. The proposed RCP-FRTF method provides better performance in terms of PSNR, computational time, complexity and accuracy as compared to conventional methods.*

Keywords: *Color-balanced, Piecewise-contrast, Retinex,Reinforced Trilateral Filter*

I. INTRODUCTION

One of the most preliminary elements in marine and ocean research that assist subsea exploration with the objective of studying marine biology and investigate geological environment is underwater image. During the acquisition of images, degradations are said to occur. Due to the presence of degradation, the quality of the image decreases, and also make it a more complicated process during the analysis.

Yi Wang et al. introduced a novel underwater image restoration method called Adaptive attenuation-curve prior depends on non-local prior [1]. Every pixel values were divided into unique clusters in RGB space. Based on a power function, every pixel values in each cluster were divided on a curve followed by attenuation in water with differing degrees. To compensate for transmission, the attenuation factor was calculated. In addition with the objective of intercepting over saturation and minimize the noise of recovered images, saturation constraints were also presented to fine-tune the transmission of three different color channels. With the principles followed, both the computational time and error was found to be reduced. However, the attenuation factor involved only the ratios between the color channels (i.e. color range domain) and ignoring the spatial domain, therefore compromising on computational complexity. To address this issue, in this work, both the color range domain and spatial domain are concerned during color correction by applying Retinex Color Constancy model. In this manner, the computational complexity is said to be reduced. Also, though oversaturation was prevented and noise present in the recovered images were found to be reduced, color balanced output was not ensured. In order to resolve this issue, a color corrected white balanced image was performed based on eigen values and eigen vectors. Thus it minimizes the computational time involved in image enhancement. C.Sanchez-Ferreira et al. presented Bio-inspired optimization metaheuristics which estimates model metrics based on physical attributes [2]. By applying the No-Reference Image Quality metric (NR-IQA), the cost function was evaluated. With search space includes unknown topology, multimodal and multidimensional characteristics, metaheuristics set were utilized as optimization techniques. The metaheuristics set are, Repulsive–Attractive Particle Swarm Optimization (RAPSO), Artificial Bee Colony (ABC), Opposition-Based Artificial Bee Colony (OABC), and Differential Evolution (DE). The light propagation is not performed to every color channel based on its wavelength and restoration process. Depends on model weights for every color channel, a color compensation process was designed. With this, the method offers a good visual quality of restored images.However, the color and visibility was said to be compromised due to the presence of haze. To address this issue, in this work, a de-haze model based on spatial and tonal filter, called as, Fuzzy Reinforced Trilateral filter model is designed. With this model, not only the color and visibility are said to be improved but also the accuracy of underwater image is said to enhance.In this work, we introduce a method to de-haze underwater images.

Manuscript published on November 30, 2019.
* Correspondence Author
A.Parameswari*, Ph.D. Research Scholar, Department of Computer Science, Bharathiar University, Coimbatore, India. Email: paramsram@gmail.com
Dr. M.V.Srinath, Director,Department of MCA, STET Women's College, Sundarakkottai, Mannargudi, Tamil Nadu, India. E-mail: sri_induja@rediffmail.com

By considering the color range domain and spatial domain, the issues of computational complexity was resolved, during the color correction and choosing the suitable white balancing method based on eigen values and vectors of corresponding domains. Moreover, to avoid bias towards color and visibility in the underwater images,

we propose to use de-haze model based on spatial and tonal filter to provide restored underwater images with good visual quality. We use piecewise linear color contrast to minimize attenuation. Finally, to ensure that the enhanced de-hazed underwater image is obtained as output, we introduce a Fuzzy Reinforced Trilateral filter to generating artifacts, to ensure underwater object detection exactness.

The major contribution of this work are (i) a Retinex Eigen-based Color Balanced model for color correction and white balancing of underwater images using Retinex Eigen Color Constancy, therefore reducing the computational complexity and time; (ii) a Piecewise Linear Color Contrast model to enhance the contrast, as a result attenuation is minimized and enhance the PSNR rate; (iii) a Fuzzy Reinforced Trilateral filter model ensure underwater object detection accuracy with different image sizes to calculate de-hazing level. This paper is ordered as follows**.** Section 2 reviews the related works. In section 3, the proposed RCP-FRTF method is detailed with neat block diagrams. In section 4, experimental results with detailed qualitative and quantitative analysis are presented. Finally, Section 5 concludes the paper.

II. RELATED WORKS

The conventional image correction, white balancing method with image de-hazing methods are discussed in this section. But, the absorption and scattering issues needs to be addressed. Simon Emberton et al. used the semantic white balancing approach to improve visibility in images and videos [3]. However, the absorption and scattering being the main problems, certain large capacity of information were compromised. Yanlong Li et al. analyzed the spatial correlation in underwater images and reduced the error rate [4]. Yan Wang et al. designed multiple linear regression model with the objective of providing qualitative measure [5]. However, certain amount of turbidity and color distortion were not removed. Jingyu Lu et al. who designed a Dark Channel Prior (DCP) algorithm not only to ensure flexibility but also to improve image restoration performance [6]. Due to occurrence of optical absorption and scattering, Target detection of underwater images is considered to be the most demanding issue. Heng Tian et al. designed a Rapid underwater target enhancement method with polarimetric imaging [7]. A linear model was introduced by Bashar Elnashef and Sagi Filin to enhance accuracy with minimal time [8]. However, with reduced visibility and imaging distance, the accuracy was found to be less. Ying Zhang et al. used Compressed Sensing Ghost Imaging via bucket detector, therefore, improving its robustness [9]. Liming Yang applied unpolarized illumination for visibility enhancement [10]. Throughout the previous couple of years, a victorious up-gradation has been initiated towards the improvement of underwater images. Diksha Garg et al. developed Contrast Limited Adaptive Histogram Equalization (CLAHE) for enhancement of underwater image [11]. With this CLAHE, root mean squared error and entropy was found to be lesser. However, natural color that forms the basis of human visual was not perceived. Chong Tang et al. proposed multi-scale Retinex that perceived natural colors adoption and by applying the Gaussian filter, the processing speed was also found to be higher [12]. Bo Wang and Chongyi Li designed a method for color correction and contrast enhancement of underwater images with retinal mechanism [13]. However due to the presence of hazy images, image contrast was said to be compromised for turbid medium conditions. Yan-Tsung Peng et al. proposed an image restoration method via Image Formation Model (IFM) and Dark Channel Prior (DCP) [14].

Ajisha Mathias and Dhanalakshmi Samiappan introduced a Diffraction Bounded Image Formation model (DB-IFM) for underwater image restoration [15]. But, the image degradation said to occur. Ji Tingting and WANG Guoyu designed an image structural decomposition algorithm for the improvement of image contrast, brightness and image fidelity [16]. Despite accuracy, error was said to occur due to higher attenuation rate. Sonali Sankpal and Shraddha Deshpande used Rayleigh scattering and maximum likelihood estimation to minimize the rate of attenuation [17]. Seiichi Serikawa and Huimin Lu presented a fast joint trigonometric filter de-hazing algorithm to lessen the noise level and enhance the edges [18]. Jianjiang Zhu et al. designed affine transformation for real time applications involving underwater images [19]. Marino Mangeruga et al. reviewed many underwater image algorithms under different environmental conditions [20].

In the literature discussed above, some models are computationally complex and certain other methods are computationally simple that are found to be easily applicable for several real time applications. However, these methods use certain assumptions to reduce the complexity which may degrade the performance or the rate of underwater detection accuracy. Hence it necessitates in designing a method that is found to be both computationally efficient and has improved rate of accuracy. With this objective in this work, Retinex Color-balanced Piecewise-contrast and Fuzzy Reinforced Trilateral Filter (RCP-FRTF) method for underwater image enhancement is designed and elaborated in the forthcoming sections.

III. RETINEX COLOR-BALANCED PIECEWISE-CONTRAST AND FUZZY REINFORCED TRILATERAL FILTER

In this section, a RCP-FRTF method is presented for underwater image enhancement. In the RCP-FRTF method, the underwater image is captured and represented in RGB color model. The block diagram of RCP-FRTF method is portrayed in Fig.1.

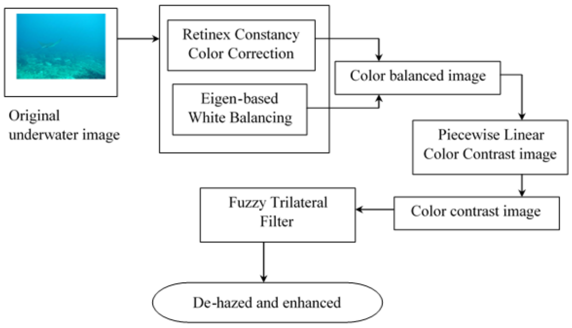

Fig.1. Block diagram of RCP-FRTF method

As illustrated in Fig.1.for implementing color balanced image, the color correction and white balancing is performed by applying a Retinex Constancy model followed by the Eigen formulation. After obtaining color balanced image, piecewise linear function is evolved and computed for each four segments separately. Finally, a de-hazed and enhanced image is obtained via Fuzzy Trilateral Filter model

A. *Retinex Eigen-based Color Balanced model*

Initially, the color correction is applied to original underwater image to eliminate the color casts and create natural outlook. The proposed color correction algorithm works based on the Retinal color constancy model. A region of underwater image includes different depths, results in various degradation level of underwater image. Therefore, the underwater image attenuation was varied for color range domain [2] and in spatial domain. To address this issue in this work, color correction of underwater image via Retinex Color Constancy model is designed. The pseudo code representation of Retinex Eigen Color Constancy algorithm is given below.

// Retinex Eigen Color Constancy algorithm

Input: underwater image '$I = I_1, I_2, \ldots, I_n$', luminance '$L(a,b)$', reflection '$R(a,b)$', weights '$W_i = W_1, W_2, \ldots, W_n$'

Output: Color Balanced image '$I_{CC}(a,b)$'

Step 1: **Initialize** luminance, reflection, weight
Step 2: **Begin**
Step 3: **For** each underwater image 'I'
Step 4: Obtain observed pixel in underwater image 'I'
Step 5: Obtain multiple proportions 'MPR' by applying different weights
Step 6: Perform retinex-based color correction
Step 7: Obtain eigen-based white balanced image
Step 8: **Return** color balanced image ($I_{CC}(a,b)$)
Step 9: **End for**
Step 10: **End**

Algorithm 1: Retinex Eigen Color Constancy algorithm

As given in Algorithm 1, the proposed method utilizes retinex framework which calculates the illumination according to observed image. Let us assume that the image being observed is split into two elements as expressed below.

$$Log[I(a,b)] = Log\ [L(a,b)] + Log\ [R(a,b)] \quad (1)$$

From the equation (1), the observed pixel in underwater image 'I' at position 'a, b' is split into two elements, i.e. elements of luminance represented by '$L(a,b)$' and elements of reflection represented by '$R(a,b)$' respectively. The major intention for design of color constancy model is to attain '$R(a,b)$' element from observed underwater image '$I(a,b)$'. Here, the element in original underwater image '$I(a,n)$' is proximate by applying different weights as expressed in the equation given below.

$$R_{MPR}(a,b) = \sum_{i=1}^{n} W_i * Log\,[I(a,b)] \quad (2)$$

From the equation (2), 'n' indicates the number of proportions with 'W_i' denotes weights with multiple proportions 'MPR' being handled with various details at various levels in underwater image. Three proportions are suitable to represent small, large and intermediate proportions. As a result, three proportionate weights are employed for these three proportions. For multi-channel images, 'MPR' is executed for each channel respectively. After that, a color correction step creates the color proportionate closer to original underwater image and shown in equation below.

$$R_{CC}(a,b) = Merge\left[I_{CC} * R_{MPR(i)}(a,b)\right], where\ i = \{R,G,B\} \quad (3)$$

$$I_{CC} = I(a,b)/(\lambda * \mu/\mu\_ref) \quad (4)$$

From the equations (3) and (4), the function of '$Merge$' refers to the process of merging three single channel images (i.e. red, or blue or green) into a multi-channel image (i.e. combination of red, green, combination of green, blue, combination of red, blue and so on). Finally, the color corrected image 'I_{CC}' is obtained based on the observed underwater image '$I(a,b)$', '$\mu = \{\mu_R, \mu_G, \mu_B\}$' representing the sum of each channel of underwater image, '$\mu_{ref} = \{\mu_R{}^2 + \mu_G{}^2 + \mu_B{}^2\}$' and '$\lambda = \{\lambda_R, \lambda_G, \lambda_B\}$' representing the highest value of each channel of the underwater image respectively.

White balancing involves a notable processing step of our method that focus at distinguishing the actual colors of the underwater images irrespective of the light illuminating it. Its' vital purpose is to eliminate unreal color casts and permit white objects to appear white in the underwater image. White-balancing aims at enhancing the image outlook particularly by eliminating the unwanted color casting due to several illumination properties. With the color corrected image, white balancing is performed in this work based on the eigen value and eigen vectors with the objective of reducing the computational time involved. Fig.2. shows the block diagram of Retinex Eigen-based Color Balanced model.

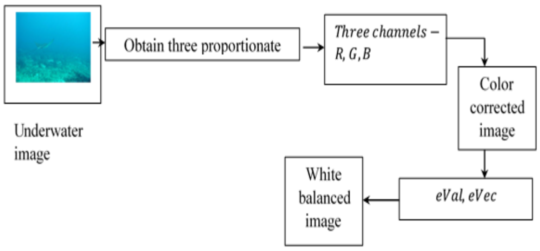

Fig. 2. Block diagram of Retinex Eigen-based Color Balanced model

From Fig.2.the proposed method utilizes the Retinex Eigen Color Constancy algorithm to eliminate the color casts in underwater input image and attain color corrected image. After that, the color corrected image is employed to estimate the illumination properties based on the eigen values and vectors. The color balanced image based on eigen values and eigen vectors are expressed as given below.

$$I_{WB}(a,b) = eVal * I_{CC}(a,b) + eVec \qquad (5)$$

$$I_{CC}(a,b) = [O_{red}(a,b), O_{green}(a,b), O_{blue}(a,b)]^{eVec} \qquad (6)$$

From the equations (5) and (6), the white balanced image '$I_{WB}(a,b)$' is obtained based on the eigen values '$eVal$', eigen vectors '$eVec$' and the grey scale value for RGB '$I_{CC}(a,b)$' respectively.

B. *Piecewise Linear Color Contrast model*

With the color balanced (i.e. color corrected and white balanced) model, nevertheless, low contrast and blurriness still prevail in the color balanced image. This is due to the reason that the scattering of light generates light rays to disseminate in water that reduces the light striking rate on the underwater images. This causes attenuation, reducing to differentiate between the objects in the color balanced images. Therefore, the contrast of the color balanced image which marks the existent of various objects in an image is reduced to a great extent. Hence, in this work, a Piecewise Linear Color Contrast model is used to improve the contrast to a better level. The pseudo code representation of Piecewise Linear Color Contrast algorithm is given below.

// Piecewise Linear Color Contrast algorithm
Input: Color Balanced image '$I_{CC}(a,b)$'
Output: Color Contrast Image ($I_{CCon}(a,b)$)
Step 1: **Begin**
Step 2: **For** each Color Balanced image '$I_{CC}(a,b)$'
Step 3: Obtain Four Segment-Piecewise Linear Function
Step 4: Measure two linear segments
Step 5: Measure color contrast image with pixel representations 'a' and 'b'
Step 6: **Return** color contrast image ($I_{CCon}(a,b)$)
Step 7: **End for**
Step 8: **End**

Algorithm 2: Piecewise Linear Color Contrast algorithm

With the Piecewise Linear Color Contrast algorithm as given above, to obtain a better enhanced image, a Piecewise Linear Color Contrast model based underwater image is enforced in this section. A Piecewise Linear Function with four segments is given below.

$$f(I_{CC}) = \begin{cases} -I_{CC} - 3 & if\ I_{CC} \le -3 \\ I_{CC} + 3 & if -3 < I_{CC} < 0 \\ -2I_{CC} + 3 & if\ 0 \le I_{CC} < 3 \\ 0.5I_{CC} - 4.5 & if\ I_{CC} \ge 3 \end{cases} \qquad (7)$$

With the above said Piecewise Linear Function (7), with four segments, the graph of this function is represented in Fig.3.is given below. As the graph of a linear function is a line, the graph of a Piecewise Linear Color Contrast model comprises of line segments, with the 'I_{CC}' values in the above example is '-3', '0' and '3'.

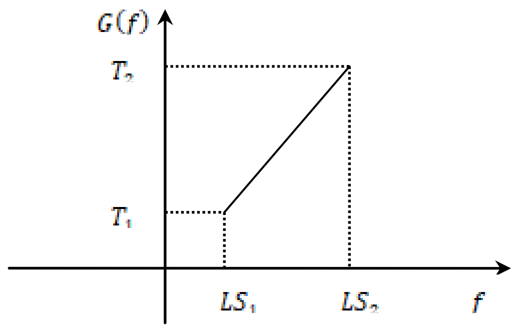

Fig.3.Graphical representation of Continuous Piecewise Linear Color Contrast

With the color corrected image as input 'I_{CC}', the piecewise linear function is expressed as given below.

$$G(I_{CC}) = aI_{CC} + b \qquad (8)$$

From the equation (8), the piecewise linear function refers to the summation of the two pixel values 'a' and 'b' of the color corrected image 'I_{CC}' respectively. The two linear segments 'LS_1' and 'LS_2' measured at two different time intervals 'T_1' and 'T_2' is expressed as given below.

$$[LS_1, LS_2] = [T_1, T_2] \qquad (9)$$

$$G(I_{CC}) = (I_{CC} - LS_1) * \frac{(T_2 - T_1)}{(LS_2 - LS_1) + T_1} \qquad (10)$$

From the equations (9) and (10), the color contrast image with pixel representations 'a' and 'b' at two time intervals 'T_1', 'T_2' is expressed as given below.

$$a = \frac{(T_2 - T_1)}{(LS_2 - LS_1)} \qquad (11)$$

$$b = T_1 - LS_1 * \frac{(T_2 - T_1)}{(LS_2 - LS_1)} \qquad (12)$$

C. *Fuzzy Reinforced Trilateral filter model*

Finally, with the color balanced and color contrasted image, a novel model is applied in this work for underwater image de-hazing using Fuzzy Reinforced Trilateral filter model to capture both the spatial and tonal filter across the image. First, a Fuzzy Reinforced model is applied to each color balanced and color contrasted underwater image to produce a smoothed view. These resultant images are then combined with Trilateral filter model to produce a de-hazed underwater image with higher amount of accuracy. The pseudo code representation of Fuzzy Reinforced Trilateral De-hazed algorithm is given below.

//Fuzzy Reinforced Trilateral De-hazed algorithm
Input: Color Contrast Image ($I_{CCon}(a,b)$)
Output: De-hazed and Enhanced output image
Step 1: Begin
Step 2: For each Color Contrast Image ($I_{CCon}(a,b)$)
Step 3: Obtain membership function for RGB color channel
Step 4: Measure reinforced fuzzy operators
Step 5: Evaluate attenuating parameters
Step 6: Return (De-hazed and enhanced output image)
Step 7: **End for**
Step 8: **End**

Algorithm 3: Fuzzy Reinforced Trilateral De-hazed algorithm

As given in Algorithm 3 Fuzzy Reinforced Trilateral De-hazed algorithm, with the Color Contrast Image as input, the objective remains in obtaining De-hazed and enhanced output image with maximum accuracy. The membership function for RGB color channel is first obtained and expressed as given below.

$$\mu_R = I_{CCon} * \frac{R - MIN(R)}{MAX(R) - MIN(R)} \qquad (13)$$

$$\mu_G = I_{CCon} * \frac{G - MIN(G)}{MAX(G) - MIN(G)} \qquad (14)$$

$$\mu_B = I_{CCon} * \frac{B - MIN(B)}{MAX(B) - MIN(B)} \qquad (15)$$

From equations (13), (14) and (15), the membership function with the reinforced model is utilized to enhance the color and contrast and therefore de-hazing the underwater image ultimately. The reinforced fuzzy operators are measured by the following formulae given below.

$$AF_R = \begin{cases} \mu_R(a,b); if\ \mu_R(a,b) \le \alpha_R \\ 1 - \mu_R(a,b); Otherwise \end{cases} \qquad (16)$$

$$AF_G = \begin{cases} \mu_G(a,b); if\ \mu_G(a,b) \le \alpha_G \\ 1 - \mu_G(a,b); Otherwise \end{cases} \qquad (17)$$

$$AF_B = \begin{cases} \mu_B(a,b); if\ \mu_B(a,b) \le \alpha_B \\ 1 - \mu_B(a,b); Otherwise \end{cases} \qquad (18)$$

From the equations (16), (17) and (18), 'α_R', 'α_G' and 'α_B' corresponds the attenuating parameter utilized for processing of image pixels 'a, b' for the corresponding images 'I_{CCon}' respectively. The attenuating parameter used in this work is set based on the trilateral filter. Here, trilateral filter refers to both the spatial and tonal scale values. The restored and enhanced image is expressed is generated using the attenuating parameters based on trilateral filter is expressed as given below.

$$\alpha_R = AF_R + \left[\frac{1}{2} e^{\frac{-(a-b)(a-b)}{2\sigma^2}} + \frac{1}{2} e^{\frac{f(a)-f(b)}{2\sigma^2}} + AVG(a+b)\right] \qquad (19)$$

$$\alpha_G = AF_G + \left[\frac{1}{2} e^{\frac{-(a-b)(a-b)}{2\sigma^2}} + \frac{1}{2} e^{\frac{f(a)-f(b)}{2\sigma^2}} + AVG(a+b)\right] \qquad (20)$$

$$\alpha_B = AF_B + \left[\frac{1}{2} e^{\frac{-(a-b)(a-b)}{2\sigma^2}} + \frac{1}{2} e^{\frac{f(a)-f(b)}{2\sigma^2}} + AVG(a+b)\right] \qquad (21)$$

With the application of the above said attenuating parameters, separate for three channels using equations (19), (20) and (21), an enhanced de-hazed output underwater image is obtained with higher rate of accuracy.

IV. EXPERIMENTAL EVALUATION

The experimental analysis of RCP-FRTF method is conducted in MATLAB R2012a of Intel core 2 duo processor and 2 GB RRAM and 320 GB hard disk capacity with Ocean Dark dataset [21]. The Ocean Dark dataset includes 183 underwater images of 1280 x 720 pixels captured via the video cameras positioned in profound depths using artificial lighting. The dataset helps the researchers in understanding the scenes with sub-optimal lighting through offer the variety of real-world instances, allowing creation of enhancement methods. RCP-FRTF method is evaluated with different metrics namely PSNR, Computational time, computational complexity and accuracy with different number of images and sizes. Comparison is made with two existing methods, Adaptive attenuation-curve prior [1] and Bio-inspired optimization metaheuristics [2]. For fair comparison, same number of images with similar sizes is used.

A. *Qualitative results and discussion*

The major objective of underwater image enhancement is fusion of color correction, white balance, color contrast and enhanced de-hazed image. The observation comprises the capability of methods to lessen the noise via color balancing, color contrasting and de-hazing models. Fig.4. shows the effect of de-hazing is shown on the histogram of images.

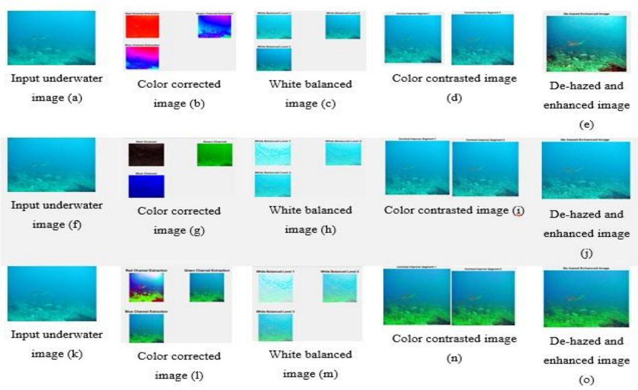

Fig.4. (a) RCP-FRTF underwater input image (b) Color corrected image (c) White balanced image (d) Color contrasted image (e) De-hazed image (f) Adaptive

attenuation-curve prior underwater input image (g) Color corrected image (h) White balanced image
(i) Color contrasted image using Adaptive attenuation-curve prior (j) De-hazed image (k) Bio-inspired optimization metaheuristics underwater input image (l) Color corrected image (m) White balanced image (n) Color contrasted image (o) De-hazed image

As given in the Fig. 4.same input underwater images are provided as input for the proposed RCP-FRTF (Fig.4.(a)) and the existing two methods, Adaptive attenuation-curve prior [1] and Bio-inspired optimization metaheuristics [2] (Fig.4(f) and Fig.4.(k)) respectively. To this input image, three different methods are applied for fair comparison. At first, Retinex color constancy is utilized to input underwater images to create color corrected images as shown in Fig.4.(b). Eigen vectors are applied to eigen values to attain white balanced images in Fig.4. (c). Next, the piecewise linear color contrast is applied in color balanced image to achieve color contrasted images as in Fig.4. (d). Finally, by applying the Fuzzy Reinforced Trilateral filter model to the contrasted image, the de-hazed and enhanced image is produced in Fig.4. (e).

Next, adaptive attenuation-curve prior method is applied in underwater image to create color corrected image as in Fig.4. (g). Next, to the color corrected image, water light estimation is applied to produce the white balanced image as in Fig.4. (h). Third, by estimating the transmission and initial relative transmission, color contrasted image is obtained as shown in Fig.4. (i). Finally, to the color contrasted image, by adjusting the transmission of three color channels, a de-hazed image is obtained in Fig.4. (j)

Third, Bio-inspired optimization metaheuristics method is used in input underwater image to create color corrected image as in Fig.4. (l). Then the image quality metric create a white balanced image as in Fig.4. (m).After that, cost function is applied in color balanced image to produce color contrasted image as in Fig.4. (n). Finally, de-hazed image is obtained using optimization process resulting in Fig.4. (o).

From the Fig.4. the final de-hazed enhanced image obtained using the RCP-FRTF method is found to be better than the existing methods [1] and [2]. This is because of the reason that using Adaptive attenuation-curve prior [1] though fine-tuning of transmission of three channels was said to be ensured, color balancing was not ensured. Besides by using Bio-inspired optimization metaheuristics [2], color compensation process, restored images were obtained with a good visual quality. However, with the presence of haze, accuracy of underwater image detection was not ensured. But the proposed RCP-FRTF method enhances the contrast and eliminates the noise for color correction and white balancing. Finally, de-hazing of image was said to be ensured via Fuzzy Trilateral Filter. Depends on visual observation, the proposed RCP-FRTF method provides better enhancement in the image contrast with de-hazed and enhanced image than the conventional methods. Underwater image is distinguished from the background, showing better utilization than the existing methods [1] and [2].

B. *Quantitative results and discussion*

In this section, the experimental results and discussion of four different metrics namely, PSNR, CT, Computational complexity and accuracy with different number of images and sizes of images are performed.

1. Impact of PSNR

PSNR measured as the ratio of original underwater image and distorted images. PSNR is formalized as below,

$$PSNR = 10 * \log_{10}\left[\frac{R^2}{MSE}\right] \quad (22)$$

$$MSE = (I - I')^2 \quad (23)$$

From equation (22) and (23), PSNR refers to ratio of logarithmic value of maximum possible pixel value of underwater image 'R' and mean square error 'MSE'. 'MSE' refers to square difference between original underwater image 'I' and noisy image 'I''. PSNR is enhanced by combining these images with trilateral filter model.

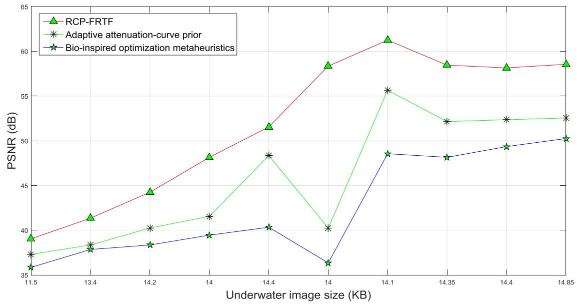

Fig.5. Convergence graph of PSNR using RCP-FRTF, Adaptive attenuation-curve prior and Bio-inspired optimization metaheuristics

Fig.5.illustrates the graphical representation of PSNR. From the above graph x axis represents the underwater image size and y axis represents the PSNR. For experimental evaluation 10 different numbers of images are considered in the range of 11.5KB to 14.85KB. For fair comparison, similar images with sizes are used to measure the PSNR for the existing Adaptive attenuation-curve prior [1] and Bio-inspired optimization metaheuristics [2]. With differing sizes of the underwater images, the PSNR also differs. On the other hand, the underwater image size is neither inversely or directly proportional to the PSNR rate. This is because of the reason that different images with different sizes are considered at several time intervals and for that set of underwater images, the rate of PSNR are measured. Comparative analysis with the existing two methods [1] and [2] shows that the PSNR rate is better when applied with the proposed RCP-FRTF method. This is due to the application of Fuzzy Reinforced Trilateral De-hazed algorithm. By applying this algorithm, both the spatial and tonal filter across the image is obtained. With this, a smoothened view is produced for each color balanced and color contrasted underwater images. Finally, by combining these images with the Trilateral filter model, the peak signal to noise ratio is said to be improved. The improvement is found to be better using the RCP-FRTF method by 13% when compared to [1] and 23% when compared to [2].

2. Impact of Computational Time

The computational time refers to the time consumed in obtaining the de-hazed underwater image with the overall samples underwater images provided as input for experimentation. The computational time is measured as given below.

$$CT = n * Time\ [De - hazing\ ] \quad (24)$$

From the above equation (24), the computational time 'CT' is measured in terms of milliseconds (ms) with 'n' corresponding to the input underwater images provided as sample. Lower the de-hazed underwater image time more efficient the method is said to be.

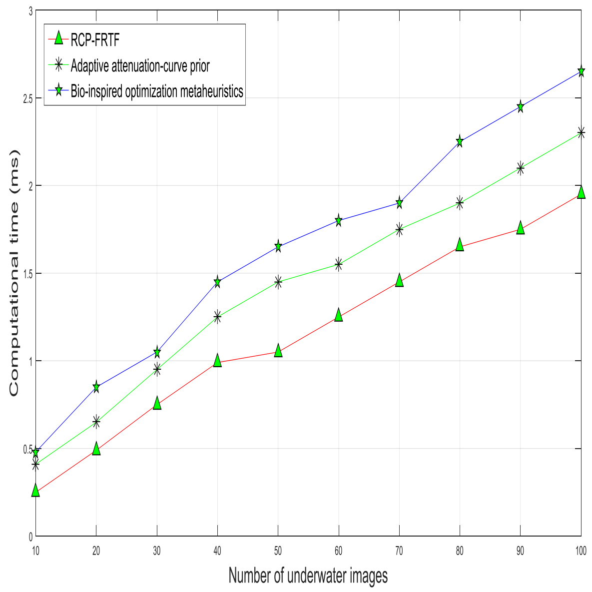

Fig.6. Convergence graph of computational time using RCP-FRTF, Adaptive attenuation-curve prior and Bio-inspired optimization metaheuristics

Fig.6.illustrates the graphical representation of computational time. In Fig.6. x axis represents the varying numbers of underwater images and y axis represents the computational time. For fair comparison between the existing and proposed methods for measuring the computational time, underwater images in the range of 10 to 100 are considered for experimentation. From Fig.6. it is evident that the number of underwater images is directly proportional to CT. While increasing the number of underwater images, the time taken for de-hazed images also improved. However, comparative analysis shows that the computation time is found to be comparative lesser using the RCP-FRTF when compared to the existing Adaptive attenuation-curve prior [1] and Bio-inspired optimization metaheuristics [2]. This is because of the application of Retinex Eigen Color Constancy algorithm. By applying this algorithm, a fusion of both color correction and white balancing is performed. First by using the Retinex model, illumination is observed. With this observed illuminated image, luminance and reflected image are obtained to which color correction step is applied for making color proportionate closer to original image. To this, a balancing is performed on the basis of eigen value and eigen vectors. With this, the time consumed in obtaining the enhanced output is found to be less using the RCP-FRTF method by 21% compared to [1] and 32% compared to [2] respectively.

3. Impact of Computational Complexity

The computational overhead refers to the memory consumed in obtaining the de-hazed underwater image with the overall samples underwater images provided as input for experimentation. The computational overhead is measured as given below.

$$CO = n * MEM\ [De - hazing\ ] \quad (25)$$

From the above equation (25), the computational overhead 'CO' is measured in terms of Kilo Bytes (KB) with 'n' corresponding to the input underwater images provided as sample. Lower the de-hazed underwater image memory more efficient the method is said to be.

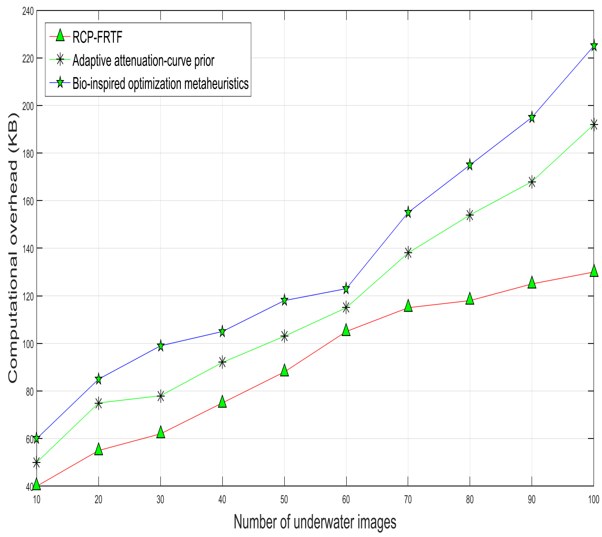

Fig.7. Convergence graph of computational complexity using RCP-FRTF, Adaptive attenuation-curve prior and Bio-inspired optimization metaheuristics

Fig.7. illustrates the computational complexity with respect to 100 different number of images of varying sizes. Graphical representation shows two dimensional axis, with x axis representing the underwater images and y axis representing the computational overhead measured in terms of kilobytes (KB). From Fig.7.it is evident that number of underwater images is directly proportional to computational overhead. While increasing the number of underwater images, the computational complexity for different images also improved. Betterment is found to be observed using the RCP-FRTF method when compared to Adaptive attenuation-curve prior [1] and Bio-inspired optimization metaheuristics [2]. This is because of the application of Piecewise Linear Color Contrast algorithm. By applying this algorithm, a color contrast is applied to the color balanced underwater image based on the piecewise linear model. With this piecewise linear model, four segments are used in a graph to obtain the line segments at different time intervals. Then, a summation is obtained only for the color balanced model, therefore reducing the computational complexity involved in obtaining enhanced underwater image using RCP-FRTF method by 21% when compared to [1] and 31% when compared to [2].

4. Impact of underwater object detection accuracy

Underwater object detection accuracy refers to the percentage ratio of number of underwater images correctly detected to the overall samples provided as input for experimentation. The underwater object detection accuracy is measured as given below.

$$A = \frac{\text{Number of underwater images correctly detected}}{n} * 100 \quad (26)$$

From the above equation (26), the underwater object detection accuracy 'A' is measured in percentage (%) with 'n' corresponding to the input images provided as sample. Higher the underwater object detection accuracy more efficient the method is said to be.

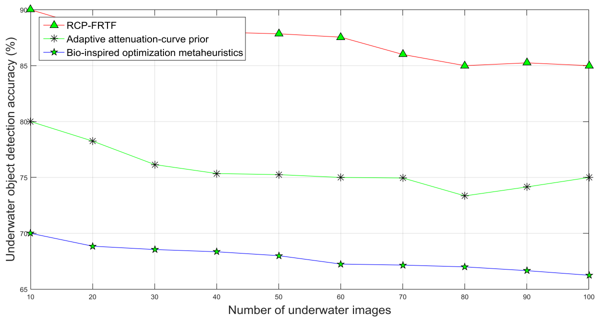

Fig.8. Convergence graph of underwater object detection accuracy using RCP-FRTF, Adaptive attenuation-curve prior and Bio-inspired optimization metaheuristics

Figure 8 given above shows the convergence graph of underwater object detection accuracy using the three different methods. For fair comparison same number of images and sizes are used to compare the underwater object detection accuracy for three different methods. The graphical representation shows improvement of accuracy using RCP-FRTF when compared to Adaptive attenuation-curve prior [1] and Bio-inspired optimization metaheuristics [2]. This is due to the incorporation of Fuzzy Reinforced Bilateral De-hazed algorithm. By applying this algorithm, membership function for RGB color channel for the color contrasted image is measured. With this measured pixel values, reinforced fuzzy operators are obtained based on the attenuating parameter utilized for processing of image pixels of varying size. Here, separate attenuating parameters are used for three channels separately. In this way, an enhanced, de-hazed image is obtained. Therefore, the underwater image detection accuracy using the RCP-FRTF method is improved by 15% when compared to [1] and 28% when compared to [2].

V. CONCLUSION

In this paper, we propose a RCP-FRTF method to address the key issues of underwater object recognition, namely color range domain, spatial domain, color and recognition visibility of different objects. At first, retinex color constancy is applied to the objective image by means of multiple proportions depending on different weights resulting in color corrected image. Next, white balanced image is obtained based on the eigen value and vectors. Then, with these color corrected and white balanced image features, color balanced image is acquired. Finally, according to the Piecewise Linear Function a color contrast image is obtained with which by applying trilateral filter, a de-hazed and enhanced image is produced. Experimental results evident that RCP-FRTF method well recognizes and locates various underwater objects, namely mine-like objects and triangle like objects, and attain demands of real-time application.

REFERENCES

1. Yi Wang, Hui Liu, Lap-Pui Chau, "Single Underwater Image Restoration Using Adaptive Attenuation-Curve Prior", IEEE Transactions on Circuits and Systems I: Regular Papers (Volume: 65, Issue: 3, March 2018).
2. C. Sánchez-Ferreira, L.S. Coelho, H.V.H. Ayala, M.C.Q. Faria, C.H. Llanos, "Bio-inspired optimization algorithms for real underwater image restoration", Signal Processing: Image Communication, Elsevier, May 2019.
3. Simon Emberton, Lars Chittka, Andrea Cavallaro, "Underwater image and video dehazing with pure haze region segmentation", Computer Vision and Image Understanding, Elsevier, Aug 2017.
4. Yanlong Li, Hongbing Qiu, Xiao Chen, Jielin Fu, Mohammed Musa, Xiaoji Li, "Spatial correlation analysis of imaging MIMO for underwater visible light Communication", Optics Communications, Springer, Mar 2019.
5. Yan Wang, Na Li, Zongying Li, Zhaorui Gu, Haiyong Zheng, Bing Zheng, Mengnan Sun, "An imaging-inspired no-reference underwater color image quality assessment metric", Computers and Electrical Engineering, Elsevier, Dec 2017.
6. Jingyu Lu, Na Li, Shaoyong Zhang, Zhibin Yu, Haiyong Zheng, Bing Zheng, "Multi-scale adversarial network for underwater image restoration", Optics and Laser Technology, Elsevier, May 2018.
7. Heng Tian, Jingping Zhu, Shuwen Tan, Yunyao Zhang, Yang Zhang, Yingchao Li, Xun Hou, "Rapid underwater target enhancement method based on polarimetric Imaging", Optics and Laser Technology, Elsevier, May 2018.
8. Bashar Elnashef, Sagi Filin, "Direct linear and refraction-invariant pose estimation and calibration model for underwater imaging", ISPRS Journal of Photogrammetry and Remote Sensing, Elsevier, Jun 2019.
9. Ying Zhang, Wendong Li, Yihai Chen, Xiaoyi Su, Ya Xiao, Zhaoming Wang, "High-visibility underwater ghost imaging in low illumination", Optics Communications, Elsevier, May 2019.
10. Liming Yang, Jian Liang, Wenfei Zhang, Haijuan Ju, Liyong Ren, Xiaopeng Shao, "Underwater polarimetric imaging for visibility enhancement utilizing active unpolarized illumination", Elsevier, Dec 2018.
11. Diksha Garg, Naresh Kumar Garg, Munish Kumar, "Underwater image enhancement using blending of CLAHE and percentile methodologies", Multimedia Tools and Applications, Springer, Mar 2018.
12. Chong Tang, Uwe Freiherr von Lukas, Matthias Vah, Shuo Wang, Yu Wang, Min Tan, "Efficient underwater image and video enhancement based on Retinex", Signal, Image and Video Processing, Springer, Feb 2019.
13. Bo Wang, Chongyi Li, "A visual hierarchical framework based model for underwater image enhancement", Frontiers of Computer Science, Springer, May 2019.
14. Yan-Tsung Peng, Keming Cao, Pamela C. Cosman, "Generalization of the Dark Channel Prior for Single Image Restoration", IEEE Transactions on Image Processing (Volume: 27, Issue: 6 , June 2018)
15. Ajisha Mathias, Dhanalakshmi Samiappan, "Underwater image restoration based on diffraction bounded optimization algorithm with dark channel prior", Optik, Elsevier, Jun 2019.
16. JI Tingting, and WANG Guoyu, "An Approach to Underwater Image Enhancement Based on Image Structural Decomposition", Journal of Ocean University of China, Springer, Dec 2014.
17. Sonali Sankpal and Shraddha Deshpande, "Underwater Image Enhancement by Rayleigh Stretching with Adaptive Scale Parameter and Energy Correction", Springer, May 2019.
18. Seiichi Serikawa, Huimin Lu, "Underwater image dehazing using joint trilateral filter", Computers and Electrical Engineering, Elsevier, Nov 2013.
19. Jianjiang Zhu, Siquan Yu, Zhi Han, Yandong Tang, Chengdong Wu, "Underwater Object Recognition Using Transformable Template Matching Based on Prior Knowledge", Hindawi, Feb 2019.
20. Marino Mangeruga, Marco Cozza, Fabio Bruno, "Evaluation of Underwater Image Enhancement Algorithms under Different Environmental Conditions", Journal of Marine Science and Engineering, Jan 2018.
21. OceanDark dataset:https://sites.google.com/view/oceandark/home