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# Multiscale Retinex based color restoration of underwater images on Lab Color Space with CLAHE

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*Abstract* - **Underwater imaging and processing systems are essential during underwater explorations due to the blurriness and mixture of various dust particles and, poor light conditions. This unfavorable situation in the underwater world imposes constraints on the underwater image processing systems. The effectiveness of the underwater imaging systems will be hassle-free and highly informative if efficient algorithms are implemented for addressing underwater vulnerabilities. This paper puts forward the underwater image enhancement method based on the Multiscale Retinex (MSR) with Contrast Limited Adaptive Histogram Equalization (CLAHE) and Dark Channel Prior (DCP) techniques. Firstly, contrast of the image is improved by CLAHE technique on L channel of the Lab colorspace of the underwater image as it improves the Low contrast and uneven lighting conditions in the image would. This MSR-CLAHE image is undergone Lab to RGB colorspace conversion, then weighted image fusion with Dark Channel Prior (DCP) is performed to mitigate the haze and blur in the input image further. The simulation results show that the proposed method shows better PSNR, SSIM and UQI values than the standard methods in the underwater image processing.**

Keywords - *Underwater image, Retinex, Multiscale retinex (MSR), Dark Channel Prior (DCP), Contrast Limited Adaptive Histogram Equalization (CLAHE).*

## 1. INTRODUCTION

Underwater exploration is one of the important engineering fields to access the underwater structures and monuments, study about whereabouts and living of sea creatures, also many applications are there. Occurrence of light attenuation causes the underwater processing systems to be erroneous and constraints to effective decision making. This attenuation causes hazy, low contrast, color casting, and blurriness in the acquired underwater images and videos. These problems arise due to the different dust particles and muddiness in the water making light scattering and absorption effect on a different wavelength of the light. Many algorithms have been proposed to address these problems of the underwater system in a different approach and we propose a system to outperform the shortcomings in the underwater image processing using the retinex model with DCP in Lab Color space.

There have been noteworthy research going on in underwater image enhancement algorithms to recover the details from the different underwater environmental and illumination conditions [1]. The authors experimented on four different underwater sites with five standard contrast-based algorithms to study and evaluate the quality of enhancement algorithms. These algorithms are mainly based on the conventional histogram-based contrast enhancement algorithms. In [2] work, Dark channel prior (DCP) was proposed to enhance the underwater images as it is considered standard for treating hazy images captured in air medium. The convolutional neural network (CNN) model-based water-net method was proposed for underwater image enhancement. But for far distances, it suffers from removing backscatter in images. Also, in the paper [3], the deep learning concept with DCP was applied to underwater image enhancement. To study the performance of the algorithms, standard underwater image datasets are preferred in the experiments. In recent years, the underwater image enhancement benchmark (UIEB) is considered which contains original images (raw images) with enhanced images (reference images)[4].

Our proposed system consists of MSRCR with DCP on Lab color space along with CLAHE applied to improve the underwater images. The efficiency of the proposed work is evaluated with various recent works in this domain. Peak Signal to Noise ratio (PSNR), Universal Quality Index (UQI), and Structural Similarity Index (SSIM) are parameters used to validate the performance of the proposed work with the recent algorithms in this underwater image enhancement.

The rest of the paper discusses the following, in section II the past works related to the underwater mage enhancements are presented, section III discusses the proposed work, section IV details the simulation results on the standard datasets and section V presents the conclusion of this work.

## 2. RELATED WORKS

Retinex theory was conceptualized by Land and McCann[5] to mimic the human visual perception system to understand the scene In the work proposed by the authors [6], existing single scale retinex was extended as multiscale retinex to achieve the color constancy and dynamic range compression in the image, but limited until gray world assumption satisfied. Retinex algorithm was developed for the images that do not violate the gray world assumption. If the reflectance of all three-color bands is the same on an average, then the image is under the gray world assumption. To manage greying effect, authors [7]used MSRCR with an automated technique to choose the upper and lower clipping point which is independent of the image concerned. Hence during the enhancement process no need to depend on image-dependent parameters. Ana Belen Petro et al proposed a modified version of the multiscale retinex algorithm with chromaticity restoration (MSRCP). They applied the simplest color balance algorithm to stretch out the RGB channels. But it suffered a small scale of halo artifacts and loss of hue in the results. In the work[8], six different retinex methods were presented with a comprehensive mathematical model. Authors [4], [9] presented a fusion-based system to enhance the underwater images based on MSRCR with DCP but color retention is close to the reference images in the UIEB dataset.

In 2009, He et all presented a dehazing technique called dark channel prior [10] for hazy outdoor images to restore. Due to the similarities between outdoor hazy environments to underwater situations, Liu Chao et al applied DCP algorithm to the underwater images first time and arrived at an improvement in results[11]. Ho Sang Lee proposed an improved Dark Channel Prior algorithm for underwater images for color correction. They introduced an image-adaptive weight factor for the calculation of the transmission map of the image[12]. To suppress the blur and color deviation in the underwear image, an adaptive background light estimation method was proposed using deep learning. Usually, researchers concentrate on modifying the transmission map by the dark channel prior algorithm and background light was also computed by changing the color channel. But accuracy of the algorithm was reduced for ultraturbid images with low visibility. Another setback with this method is the larger time consumption for real-time enhancement[13]. Galdran et all presented red channel-based DCP to have faithful transmission map estimation from the red channel attenuation by water and DCP[14]. From the standard DCP, in[15] underwater DCP(UDCP) was proposed to manage the prior problem of red channels by considering blue and green channels. This method of estimation of medium transmission and backscattering light gives sufficient knowledge to enhance the image. To represent exact details of the images to the human user, it is mandatory to present the output results effectively perceivable by the human visual perception system. Among different color models in the image processing and understanding, CIE Lab is the color model deserving and mitigating the discrepancies of RGB and CMYK color models[16].

Multiscale Retinex with Color Restoration

In image enhancement, both color constancy and dynamic range compression are possible to achieve simultaneously by retinex algorithms, which follow the principle of the human visual perception system[17], [18]. The product of reflectance and illumination components from the object is considered as the image in retinex theory. To understand the illumination component of the object, it is necessary to have a piece of knowledge on reflectance. The image model can be written as an equation given below.

$$I_i(m,n) = r_i(m,n)\, S_i(m,n) \qquad (1)$$

Where $I_i(m,n) - Input\ image\ intensity\ value\ ranges\ in\ (0,255)\ at\ i-th\ color\ channel$ $r_i(m,n) - Reflectance\ of\ the\ image\ in\ (0,1)$

$S_i(m,n) - Illumination\ of\ the\ image\ in\ (0,255)$

Apply logarithm on both sides of the equation (1),

$$\log I_i = \log r_i + \log S_i \qquad (2)$$

Let Illumination is the gaussian function on the input image, the general mathematical expression for single scale retinex is given based on the equation (2).

$$R_i(m,n) = \log(I_i(m.n)) - \log(I_i(m,n) * F_i(m,n)) \qquad (3)$$

$where\ R_i(m,n)\ is\ the\ output\ image\ of\ the\ retinex\ on\ i-th\ channel$

$F_i(m,n)\ is\ the\ normalized\ gaussian\ surround\ function$

The mathematical expression of the gaussian surround function is,

$$F(m,n) = C\, e^{[-(m^2+n^2)/2\sigma^2]} \qquad (4)$$

Where σ is the standard deviation of the gaussian filter having control over spatial detail and C is the constant[19]. The trade-off with single scale retinex is either dynamic range compression or color rendition.

Multiscale Retinex (MSR) Theory:

Multiscale retinex theory is based on the human visual perception system, and maintains the balance between dynamic range compression and color constancy by calculating the weighted sum of multiple single scale retinex outputs on the input image[17], [18]. The formula for calculating the MSR is given by [19],

$$R_{MSR_i} = \sum_{n=1}^{N} w_n R_{n_i} = \sum_{n=1}^{N} w_n [\log I_i(m,n) - \log(F_n(m,n) * I_i(m,n))] \quad (5)$$

Where N represents the number of scales in MSR, wn is the weight of each scale and $F_n(m,n) = C_n\, e^{[-(m^2+n^2)/2\sigma\, n^2]}$. The values of the scales were fixed as 15, 80, and 250. But based on the grey world assumption, the RGB components' average value of the image must average out to a common grey value. If this assumption is not satisfied, there may be a dominance of any color or looks greyish in the image. To avoid this color saturation in the image, multiscale retinex with a color restoration algorithm was proposed[17], [18]

Multiscale retinex with color restoration (MSRCR):

In this, the color restoration function is multiplied to the output of MSR to get restored the color in the image. It is given by

$$R_{MSRCR_i}(m,n) = C_i(m,n) R_{MSR_i}(m,n) \quad (6)$$

where $C_i(m,n) = f\left(I_i'(m,n)\right)$ (7)

$C_i$ is the ith band of color restoration function. However, this algorithm also suffers from greyish images. There are many variations proposed to mitigate this like automated MSRCR and MSR with chromaticity preservation[17], [20].

Dark channel prior:

A dark channel prior (DCP) algorithm was proposed to handle the haziness in natural outdoor images by He et al[21]. The authors identified that there would be low-intensity pixels at any of the color channels in the image local patch. This algorithm is mainly used to dehaze the outdoor and aerial images and for the given image I, the dark channel is calculated as,

$$I^{dark}(m) = \min_{c \in \{r,g,b\}} \left( \min_{n \in \Omega(m)} (I^c(n)) \right) \quad (8)$$

Where $I^c$is a color channel of the image I and $\Omega(m)$ is the image local patch centered at m. n is the pixel in the image local patch $\Omega(m)$.

Inspired by the work[21], modified DCP was applied to underwater images to estimate the transmission and shown improvement in underwater image enhancement[22].

CLAHE

Contrast limited adaptive histogram equalization (CLAHE) is an enhanced version of the adaptive histogram equalization (AHE) method, which partitions the image into multiple regions and equalizes the grey levels in the regions. Through the adaptive histogram equalization methods, the loss of features by global histogram equalization, color distortion, and haziness could be avoided by using CLAHE.

CIE L*a*b

The results produced by the algorithms on color images should not cause systematic bias or optical illusions in human visual perception. CIE-Lab colorspace is meant to present the images of how a human visual perception system perceives the scene[23]. This L*a*b consists of three-color values: L represents the perceptual lightness, and a* and b* are red, green, blue, and yellow unique colors for human vision. This color model is the device-independent and manages the RGB and CMYK color models from the poor human perception.

## 3. METHODOLOGIES

MSRCR based Proposed Model

In this work, an underwater image enhancement technique based on MSRCR with DCP and CLAHE is proposed. The flowchart of the proposed system is shown in figure 1.

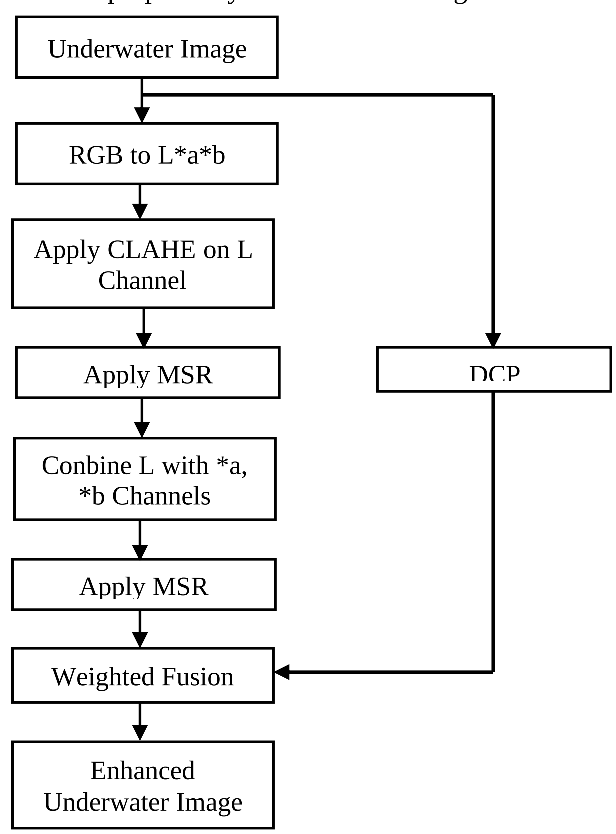


Figure 1 - Work Flow of Proposed Scheme

Firstly, the degraded underwater image is converted from RGB to CIE-L*a*b colorspace for enhancement steps. All the image enhancement processing steps are being carried out on the L channel of the image. Firstly, the MSRCR algorithm was applied to the L channel to retain the color constancy and avoid the desaturation of the image. Then DCP was employed to the improved L channel for reducing haze in the scene and CLAHE followed on it to have a contrast enhancement. The dehazed and underwater turbidity mitigated image is obtained by combining L, *a, and *b channels and converted to RGB colorspace.

Numerical results and discussion

For the validation of the proposed work, we used underwater image enhancement benchmark (UIEB) dataset images in the simulations. This UIEB dataset consists of 950 real-world underwater images and 890 of them are available with related reference images. This dataset is publicly available for researchers [4], we employed these in the proposed system to enhance the underwater images and compared our results. We used the metrics PSNR, UQI, and SSIM to validate the proposed system performance against the existing standard algorithms in underwater image enhancement.



Figure 2- Results of the various methods with Proposed Algorithms

## 4. RESULT AND DISCUSSION

Simulations of all the standard underwater image enhancement and dehazing methods and proposed algorithms were conducted on MATLAB 2020a with Windows System of 8GB RAM, 3GHz. In figure 2, output images of simulation results shown. The numerical results of the simulation tabulated on Table 1.

Table 1 Simulation Results with Standard Metrics

| Algorithms | PSNR | SSIM | UQI |
|---|---|---|---|
| SSR | 10.08 | 0.57 | 0.66 |
| MSR | 10.09 | 0.58 | 0.74 |
| MSRCR | 14.02 | 0.67 | 0.79 |
| AMSR | 14.66 | 0.85 | 0.77 |
| DCP | 16.34 | 0.82 | 0.75 |
| MSR-CLAHE | 18.72 | 0.86 | 0.81 |
| MSR-CLAHE with DCP | 22.74 | 0.91 | 0.84 |

From the above table, it is inferred that MSR-CLAHE and MSR-CLAHE with DCP outperform the existing methods in enhancement process. The enhancement level of MSR-CLAHE with DCP shows higher PSNR, SSIM and UQI values rather than the MSR-CLAHE method. Among 890 raw images in the dataset, test simulation conducted on samples of images in all the three categories of the dataset images.

## 5. CONCLUSION

The proposed method on the underwater image from the UIEB dataset, it shows that viable improvement in the contrast and dehazing quality on the images achieved. The performance metrics were considered and comparison with the standard techniques in underwater image processing also performed. It is evident that MSR-CLAHE and MSR-CLAHE with DCP gives better results. As DCP improves the dehaze in the underwater environment, MSR-CLAHE with DCP performs with better output results. In this direction, more dataset with different underwater and turbidity environments to be studied and modification in the algorithm may be devised to have better results.

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