Underwater Image Enhancement using CLAHE

G. Suresh[1], N. Vasu[2], ,[3], M. Pallavi ,K. Sudheer[4], T. Siva Ram[5]
[1,2] Department of Electronics and Communication Engineering, Aditya Engineering College, East Godavari, Surampalem

Abstract: The exploration of marine energy, protection of marine environments, military operations, and research on marine life are just a few of the recent uses of underwater images. In these applications, image acquisition is carried out at varying depths of water, and artificial light is used to capture the underwater object. Depending on the depth, organic material, currents, temperature, or other water properties, light behaves differently in water, causing the same object to appear differently. This results in shallow contrast and color distortion images. Hence, there is a need to enhance the underwater images in light of the above applications.

Many fields have used underwater images in recent years, including marine energy exploration, environment protection, military operations, and marine life research. In these applications, image acquisition is carried out at varying depths of water, and artificial light is used to capture the underwater object. Light behaves differently under water due to its physical properties, which causes it to appear different with variations in depth, organic material, currents, temperature, etc. This results in color distorted images and hazy images with very low contrast. Hence, there is a need to enhance the underwater images in light of the above applications.

Keywords:

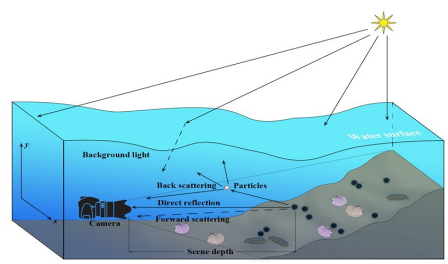
Image enhancement, CLAHE, DCP, White Balance, Global Contrast, Local Contrast, Saliency weight, Exposedness, multiscale fusion, and color correction.

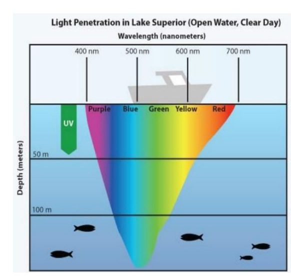
Introduction:

Water and aquatic plants encompass 71 percent of the planet's surface. There is a greater desire to learn about what is underneath the surface. The picture of deep seas nowadays has prompted a large-scale inquiry to extend the underwater for seafloor exploration and navigation. The inspection of seabed exploration and plants is part of the underwater imaging. Now it's time to move on from looking for wrecks to looking for natural resources. Because light is increasingly reduced as it travels through water, underwater photographs are characterized by poor visibility. As a result, scenes are poorly contrasted and murky. Unmanned remote vehicles are used to explore the sea floor for the reasons stated above.

Ocean engineering and scientific research, such as monitoring sea life, accessing the geological environment, and ocean rescue, rely heavily on the quality of underwater photos. The absorption and scattering properties of water, on the other hand, hinder the vision of underwater things. As a result, underwater camera images typically have low contrast, uneven illumination, blurring, bright artifacts, decreased color, noise, and other aberrations. Many algorithms for restoring colors and improving contrast in observed underwater photos have been presented. Visual inspection is utilized to evaluate the performance of image processing algorithms in the majority of these methods.

The sight distance is limited to roughly twenty meters in clear water and five meters or less in muddy water due to light attenuation. The process of light attenuation is triggered by absorption (the process of absorbing light energy) and scattering (which alters the light path's direction). The light absorption and scattering mechanisms in the entire performance of undersea vehicles are influenced by water. Systems for imaging. Forward scattering (randomly diverted light traveling from an object to the camera) causes visual details to be blurred. Backward scattering, on the other hand (the fraction of light reflected by the water towards the camera before it reaches the objects in the scene), reduces image contrast, resulting in a characteristic veil that superimposes itself on the image and hides the scene from other elements such as dissolved organic matter or small observable floating particles. Absorption and scattering effects are caused by a variety of components, including dissolved organic matter and small visible floating particles, as well as the water itself.





The proposed approach:

The figure depicts the flow chart(2) for implementing the recommended approach. The suggested method is divided into three parts: designing input images, calculating input image weights, and multiscale fusion. The first input image (input 1) is created by applying the WB algorithm to the original image to correct the color, and the second input image (input 2) is created by using the DCP algorithm to input 1 to reduce particle scattering deterioration. The third input (CLAHE) is obtained by applying the (WB+CC) and passing it to CLAHE, which becomes the third input. Then, for input 1, input 2, and input 3, compute the global contrast weight, local contrast weight, saliency weight, and exposure weight, then normalize the four weights of the two images to get the normalized weights W1, W2, and W3. Finally, normalized weights W1, W2, and W3 are utilized to fuse input 1, input 2, and input 3. A multiscale fusion method is employed to avoid unwanted halos in the output image generated by edge mutation.

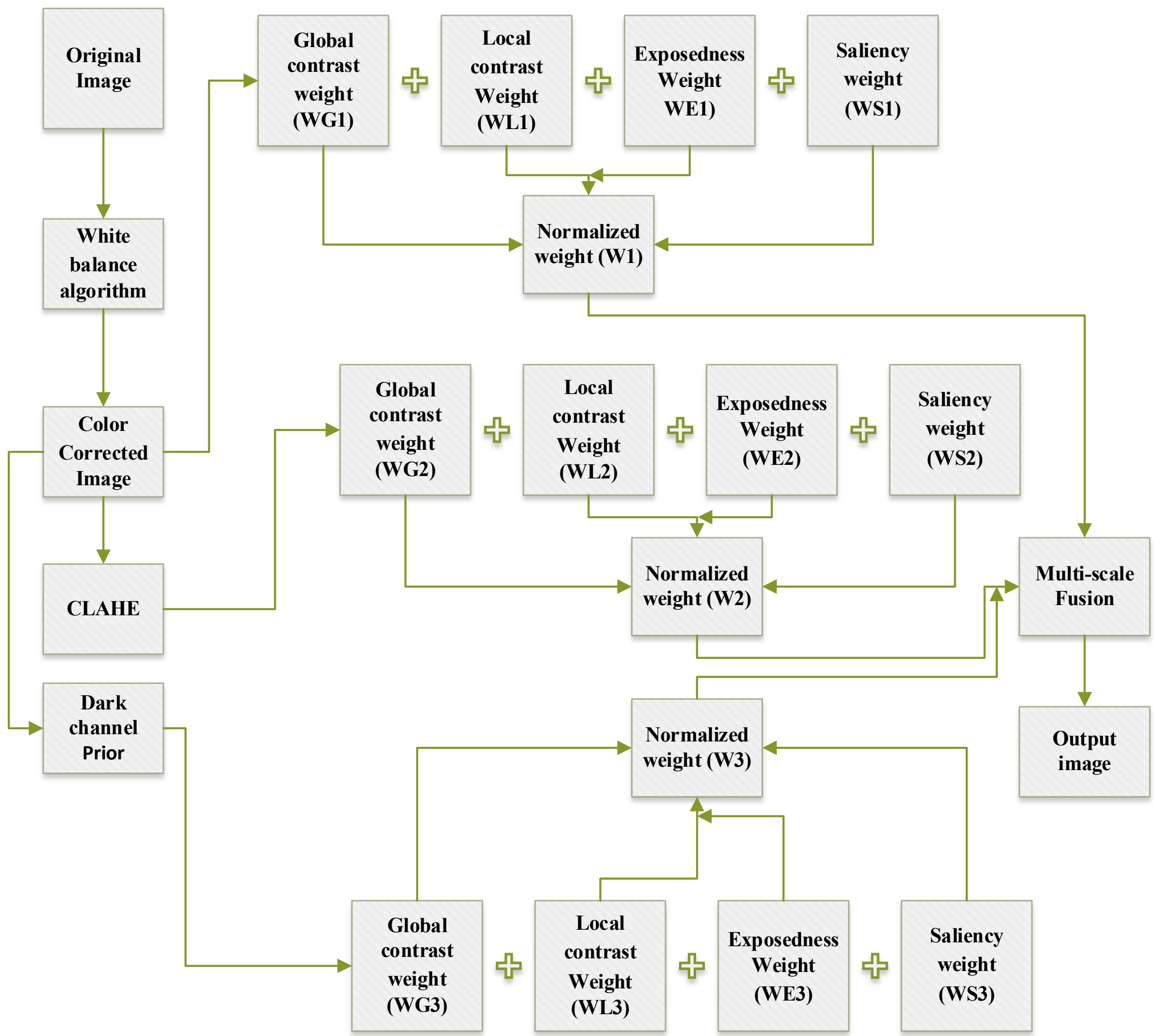


Figure 2: Flow chart of the proposed approach implementation.

STEPS FOR PROPOSED METHOD:

Step 1: Collect the images from the dataset. The Datasets used are U45, UIEB, and RUIE.
Step 2: Apply the White Balancing Algorithm for all the images in the dataset.
Step 3: Apply Color Correction
Step 4: Pass the color corrected to CLAHE and DCP Algorithm
Step 5: To calculate the Normalized weight(W1), Apply the color corrected to the Global contrast weight, Local contrast weight, Saliency weight, and Exposedness weight.
Step 6: To calculate the Normalized weight of CLAHE(W2) and DCP(W3), Apply the CLAHE and DCP to Global contrast weight, Local contrast weight, Saliency weight, and Exposedness weight.
Step 7: Finally, W1, W2, and W3 are fused by using multi-scale fusion, and the output image is obtained.

Literature review:

Codruta O. Ancuti, Cosmin Ancuti, Christophe De Vleeschouwer, Philippe Bekaert suggested Color Balance and Fusion for Underwater Image Enhancement in 2017. They used the white-balancing, Gamma Correction, and multi-scale fusion methods in which they studied light propagation in under water, underwater white balance, and multi-scale fusion and implemented underwater white balance evolution, Underwater Dehazing Evaluation.

Diksha Garg, Naresh Kumar Garg, and Munish Kumar [2] performed underwater image improvement utilizing a blend of CLAHE and percentile techniques in 2018. They developed the Contrast-Limited Adaptive Histogram Equalization (CLAHE) and Percentile techniques, claiming that the system was evaluated using two parameters: RMSE (Root Mean Squared Error) and Entropy. The larger the error, the less the accuracy produced better results than the existing techniques.

Omer Deperlioglu et al. developed a practical method for underwater image enhancement with adjusted CLAHE. They used histogram equalization and also contrast-limited adaptive histogram equalization methods. The proposed method has been evaluated by using the entropy value, PSNR (Peak Signal to Noise Ratio), and the MSE (Mean Square Error) considering some existing methods in the literature.

Meng Ge, Qingqing Hong, and Lifeng Zhang implemented a Hybrid DCT-CLAHE Approach for Brightness Enhancement of Uneven-illumination Underwater Images in 2018 with Brightness Equalization, Image Enhancement, and DCT Coefficient methods used for image brightness equalization using the DCT technique and image contrast enhancement using CLAHE algorithm.

Chongyi Li et al. developed An Underwater Image Enhancement Benchmark Dataset and Beyond They used underwater image enhancement, real-world underwater images, comprehensive evaluation, and deep learning methods in which they have constructed an underwater image enhancement benchmark dataset that offers large-scale real underwater images and the corresponding reference images.

Guzin Ulutas et al. developed Underwater image enhancement using contrast limited adaptive histogram equalization and layered difference representation published, in which they used CLAHE, LDR, Contrast correction, and Color correction methods to improve the visual quality of the underwater images. Consists of two modules - Contrast correction and Color Correction.

A Hybrid DCT-CLAHE Approach for Brightness Enhancement of Uneven-illumination Underwater Images which was implemented by Meng Ge,Qingqing Hong,Lifeng Zhang [4] in 2018 with Brightness Equalization,Image Enhancement, DCT Coefficient methods used for image brightness equalization by the means of DCT technique and image contrast enhancement utilizing CLAHE algorithm.

WB algorithm of input:

White balancing is a crucial post-production operation that tries to improve the image's appearance by removing undesired color casts caused by different illuminants. White balancing suffers from noticeable impacts in water deeper than 30 feet since the absorbed colors are difficult to restore. Furthermore, due to the poor light transmission in this sort of medium, underwater scenes have a severe lack of contrast.

Color Correction:

This parameter controls the overall brightness of an image. Enhances edges and fine details within an image. Reduces color shifting for the overall image. Consequently, in our framework, the illumination is estimated by the value μI that is calculated from the average of the scene μref and adjusted by λ

$$\mu I = 0.5 + \lambda\ \mu ref$$

Global contrast weight (GL) :

It calculates the absolute value of the filter output after applying a Laplacian filter to each input luminance channel. Because it assigns high values to edges and texture, this simple indication has been employed in a variety of applications, including tone mapping and depth of field extension.

This weight is insufficient to recover the contrast in an underwater image restoration challenge, owing to its inability to differentiate between the ramp and flat regions.

We looked for an extra contrast measurement that could examine the local distribution independently to solve this problem.

Local contrast weight (WLC):

It is made up of the relationship between each pixel and the average of its immediate surroundings. This measure has the effect of enhancing the impression of local contrast since it favors transitions in the second input's bright and shadowed areas. The (WLC) is calculated as the standard deviation between pixel brightness level and its surrounding region's local average:

$$W_{LC} = \left|\left|I^k - I^k_{wc}\right|\right|$$

where Ik represents the luminance channel of the input,Ikwc represents the low-passed version of it. The filtered version Ikwc is obtained by employing a small 5 × 5, ([1, 4, 6, 4, 1]/16) separable binomial kernel with the high-frequency cut-off value whc = π/2.75

Saliency weight (WS):

Its goal is to draw attention to distinguishing things that are lost in the underwater scene. The biological principle of center-surround contrast inspired this computationally efficient saliency technique, which is simple to implement. The saliency map, on the other hand, favors highlighted areas.

To improve the accuracy of the results, we use an exposedness map to safeguard the mid-tones, which may be affected in some circumstances. Global contrast and spatial coherence are considered in this method, which can produce a full resolution saliency map. The formulas are shown below.

$$W_{Sal}(I_p) = \sum_{\forall Ii \in ID}(I_p, I_i)$$

Exposedness weight (WE) :

It assesses how well a pixel has been exposed. This evaluated quality allows an estimator to maintain a consistent look of local contrast, which is preferably neither overdone nor understated. When the normalized values of the pixels are close to the average value of 0.5, the pixels appear to be more exposed. The distance between this weight map and the average normalized range value (0.5) is stated as a Gaussian-modeled distance:

$$W_E(x, y) = \exp(-\frac{(Ik(x, y) - 0.5)2}{2\boldsymbol{\sigma}})$$

Where I^k (x, y) is the pixel location (x, y) of the input image, and the standard deviation is set to $\boldsymbol{\sigma}$ = 0.25.

Contrast Limited adaptive histogram equalization:

Ordinary AHE tends to exaggerate contrast in areas of the image that are relatively stable. CLAHE is a type of adaptive histogram equalization in which contrast amplification is regulated to reduce noise amplification. CLAHE is used to reduce noise amplification.

For each neighborhood from which a transformation function is derived in CLAHE, the contrast limited approach must be used. Rather than collecting the entire image, CLAHE eliminates over-amplification by separating it into little data sections known as Tiles, which are subsequently contrast-enhanced.

Normalized weights:

We use normalized weight values W (given an input k, the normalized weight is derived as) to produce consistent results.

$$W^k = \frac{w^k}{\sum_{k=1}^{k} w^k}$$

Ensure that for each pixel point the sum of the weight mappings W equals one.

Multiscale fusion:

Based on the input images I1, I2 and I3, their four weight maps are extracted, respectively, to produce consistent results. To obtain the weight map W1 of I1, first sum the four weight maps of the image I1. To obtain the corresponding standardized weights in figure W, one can also obtain the weight maps W2, and W3 of the input images I2, and I3.

Then, one can normalize W1, W2, and W3 to come up with W. For the input image version, the first layer of the pyramid is obtained using the Laplace operator. Next, by down sampling the first layer, the second layer image is obtained, etc. This study sets up a pyramid with three levels. A similar algorithm produces the normalized weight version W n, corresponding to each layer of the Laplacian pyramid, by filtering the input image with the Low-Pass Gaussian kernel function G. We can express the pyramid of fusion as follows:

$$Fusion_{(i,j)} = \sum_{n=1}^{N} W_n(i,j) I_n(i,j)$$

$$pyramid^l(i,j) = \sum_{n=1}^{N} G^{1}\{W_n(i,j)\}\, L^1\{I_n(i,j)\}$$

Where $pyramid^l(i,j)$ is the level of the pyramid, N is the number of input images, G^l is the level l of the Gaussian pyramid, and L^l is the level l of the Laplacian pyramid.

Evaluation metrics:

Entropy, MSE, PSNR, SSIM, UICM, UISM, UIConM, UIQM, and UICQE are the evaluation metrics used.

Entropy:

Similarly, the entropy in Eq measures the richness of details in an image, which allows us to gain insight into the output image's quality. In the equation, we used entropy, which measures the detail in the image.

$$Entropy(x) = -\sum_{i=1}^{n} P(x_i) log P(x_i)$$

MSE and PSNR:

Measuring signal quality using Mean Square Error (MSE). By comparing two signals, the MSE can be used to determine whether the two signals are similar or distorted. A signal that is the original is usually one signal, and a signal that has been recovered from something otherwise corrupted. In mathematical terms, the MSE between the two signals is expressed in the below eq :

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(x_i - y_i)^2$$

The peak signal to noise ratio (PSNR) is calculated as follows:

$$PSNR = 10\, log_{10}(\frac{L^2}{MSE})$$

Underwater Image Colorfulness Measure (UICM):

Most underwater photographs have a significant color cast. Depending on the wavelength of the light, colors fade one by one as the depth of the water grows. The color red is the first to fade because it has a shorter wavelength. As a result, underwater photographs are typically bluish or greenish. Additionally, underwater photos suffer from extreme color de-saturation due to limited lighting circumstances.

Underwater image colorfulness is measured by the overall colorfulness metric shown in

$$UICM = -0.0268 \times \sqrt{\mu_{\alpha,RG}{}^2 + \mu_{\alpha,YB}{}^2} + 0158$$

Underwater Image Sharpness Measure (UISM):

Sharpness is a quality that refers to the ability to preserve fine details and edges. Due to forward scattering, pictures captured underwater suffer from extreme blurring. The image clarity is degraded as a result of the blurring effect.

The Sobel edge detector is initially applied to each RGB color component to measure edge sharpness. The grayscale edge map is created by multiplying the generated edge map with the source image.

Only the pixels on the margins of the original underwater image are saved this way. The enhancement measure estimation (EME) metric is well-known for its suitability for photos with a homogeneous backdrop and non-periodic patterns.

The UISM is formulated as shown in

$$UISM = \sum_{c=1}^{3} \lambda\, \text{EME}(\text{grayscale edge}_c)$$

$$EME = \frac{2}{k_l k_2}\sum_{l=1}^{k1}\sum_{l=1}^{k2} \log(\frac{I_{max,k,l}}{I_{min,k,l}})$$

Underwater Image Contrast Measure (UIConM):

It has been proven that contrast correlates with stereoscopic underwater visual performance acuity. Contrast degradation occurs in underwater photographs. Backward dispersion is generally to blame.

As shown in the following image, the contrast is determined by applying the log AMEE measure to the intensity image.

UIConM = log AMEE(Intensity)

The log AMEE in

$$\log AMEE = \frac{1}{k_1 k_2} \times \sum_{k_2}^{k_1}\sum_{k_1}^{k_2} \log\left(\frac{I_{max,k,l} \times I_{min,k,l}}{I_{max,k,l} + I_{min,k,l}}\right) log\left(\frac{I_{max,k,l} \times I_{min,k,l}}{I_{max,k,l} + I_{min,k,l}}\right)$$

UCIQE and UIQM :

A higher UCIQE score indicates that the result is more compatible with human visual perception in terms of chroma, saturation, and contrast, while a higher UIQM value implies that the result is more consistent with human visual perception.

$$UCIQE = C_1 \times \sigma_c + C_2 \times con_1 + C_3 \times \mu_s$$

where σ c, conl, and µs are the standard deviation of chroma, the contrast of luminance, and the mean of saturation.

$$UIQM = C_1 \times UICM + C_2 \times UISM + C_3 \times UIConM$$

The parameters c1, c2, and c3 are dependent on the application, e.g., more importance should be given to c1 for underwater color correction, and c2 for increasing visibility.

SSIM:

An index measuring structural similarity between two images is called the Structural Similarity Index (SSIM). As long as the other image is considered of perfect quality, the SSIM index can be viewed as a quality measure of one of the images being compared.

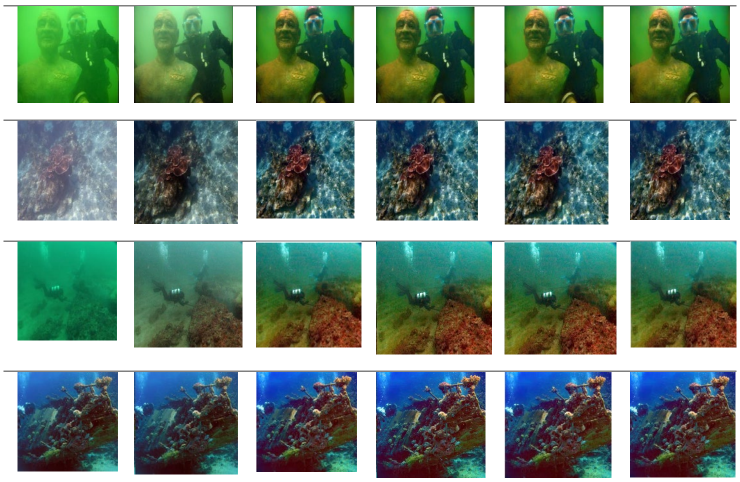
SSIM = l(x; y) * c(x; y) * s(x; y);

$$= \frac{2\mu_x\mu_y + C_1}{\mu_x{}^2 + \mu_y{}^2 + C_1} \times \frac{2\sigma_x\sigma_y + C_2}{\sigma_x{}^2 + \sigma_y{}^2 + C_2} \times \frac{2\sigma_{xy} + C_3}{\sigma_x{}^2 + \sigma_y{}^2 + C_3}$$

where μ_x and μ_y are means while σ_x and σ_y are standard deviations of the patches x and y, respectively.

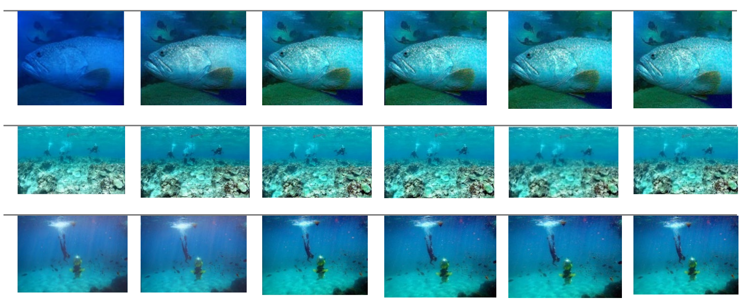
Qualitative Results:

The following images are from different datasets like U45, RUIE, and UIEB. Each block is the output of the images of different algorithms like White Balance, Color Correction, DCP, CLAHE, and finally, the fused Output image.



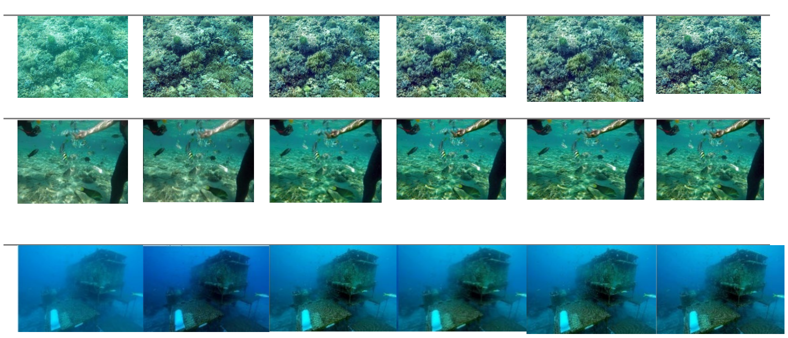
Original Image	White Balancing	Color Correction	DCP	CLAHE	Output Image

Fig 1: U45 Dataset



Original Image	White Balancing	Color Correction	DCP	CLAHE	Output Image

Fig 2: RIUE Dataset



Original Image	White Balancing	Color Correction	DCP	CLAHE	Output Image

Fig 3: UIEB Dataset

Comparative Analysis:

Our project has improved underwater image quality metrics. The following table compares some of the metrics. Several approaches and methodologies are discussed for improving underwater images.

Metric	Results from [21] reference	Proposed Method
Entropy	7.41	7.43
MSE	2199.96	2216.48
PSNR	16.467	16.55
SSIM	0.68	0.69
UICM	-60.50	-59.55
UISM	7.13	7.20
UIConM	0.75	0.78
UIQM	3.07	3.14
UICQE	0.57	0.58

Qualitative results for U45 dataset

Metric	Results from [21] reference	Proposed Method
Entropy	7.53	7.59
MSE	2078.62	2076.77
PSNR	15.94	16.17
SSIM	0.40	0.42
UICM	-33.60	-30.24
UISM	4.48	4.30
UIConM	0.78	0.80
UIQM	3.18	3.21
UICQE	0.55	0.56

Qualitative results for RUIE dataset

Metric	Results from [21] reference	Proposed Method
Entropy	7.35	7.40
MSE	1554.49	1407.55
PSNR	17.88	18.59
SSIM	0.76	0.77
UICM	-51.02	-49.33
UISM	5.28	5.17
UIConM	1.34	1.36
UIQM	4.90	5.05
UICQE	0.56	0.57

Qualitative results for UIEB dataset

CONCLUSION:

We proposed a new method to enhance the underwater images, by using the CLAHE algorithm in this project to achieve better contrast in images. We used MSE, PSNR, SSIM, UICM, UISM, UIConM, UIQM, and UICQE metrics to measure image contrast. This approach has successfully corrected the color cast and removed the haze of the underwater image, based on the qualitative results obtained. In addition to achieving the highest average UIQM value compared to those of the advanced methods, the quantitative results demonstrate that the proposed approach also maintains an excellent performance on different levels of distorted and hazy images. As a result of the experimental findings, it was found that the proposed technique outperforms classical HE by a wide margin and offers better preservation of local features, including contours and textures.

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