A Hybrid Approach with CLAHE and Dark Channel Prior for Enhancing Underwater Images

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Abstract: The underwater images (UIM) are rigorously degraded by colour deviations, scattering, and absorption. This can be addressed by enhancing the UIM. Prior knowledge of the degradation model is combined with enhancement methods to achieve superior performance. We have used a hybrid approach that incorporates the White Balancing (WB) technique for colour correction, CLAHE for enhancing contrast, and the Dark Channel Prior (DCP) method to decrease haziness in the image. Firstly, the UIM is colour corrected using WB. CLAHE is applied on a white-balanced image. DCP is also applied on white-balanced images to remove haziness. Finally, CLAHE output and DCP output are fused at a multi-scale by considering different weight maps to obtain the enhanced UIM. The U45, RUIE, and UIEB datasets are used to validate the effectiveness of the devised technique. A comparison of the developed technique with current methods reveals that the developed technique is superior.

Keywords: color correction; contrast enhancement; de-haziness; image enhancement; life underwater; underwater image

1. Introduction

Underwater imaging enables us to visualize the world underwater and can be used for various applications including marine archaeology, marine geology, oceanographic research, marine mining, etc. However, underwater images (UIM) suffer from the problem of severe depreciation of image quality. Thus, this affects their dependability and efficacy in marine applications. The physical properties of the water are a significant factor in the degradation of UIM. As light passes through a water medium, it undergoes absorption by the water itself and scattering by water particles, leading to a phenomenon known as attenuation. Absorption of light distorts the colour of UIM, scattering of light results in low contrast and blur of UIM. Hence, UIM experiences imperfections viz., colour distortion, low contrast, and hazy details. Due to the aforementioned issues, the practical applicability of underwater images is limited. As a result, underwater image enhancement has evolved into a challenging research problem.

Many researchers are working on this hot research area and the appraisal of their contributions is summarized [1)], [2)]. These methods can be divided into two primary categories: image enhancement methods (IEnM) and image restoration methods (IReM) [3)]. IReM rely on the degradation model specific to UIM conditions, and they aim to restore the image through an inverse solution of this model. Several IReMs have been devised are centered on the dark channel prior (DCP) and have seen subsequent enhancements [4)], [5)], [6)], [7)], [8)]. These IReMs suffer from the limitation of the prior degradation model and more computational resources.

On the other hand, IEnM works without prior knowledge of the degradation model and physical characteristics. Histogram equalization, Retinex and fusion strategy are mainly explored in various IEnMs. White balancing (WB) algorithm for colour correction and Contrast Limited Adaptive Histogram Equalization (CLAHE) for contrast enhancement have been utilized to leverage the UIE.

C. Ancuti et al. developed a fusion framework for UIE to fuse colour-corrected and contrast-improved images [9)]. Four maps are used in this framework to improve images

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that have been damaged by light scattering and absorption. The devised method lessens the noise by preserving the edges to support temporal coherence. J. Y. Chiang and Y. Chen devised a dehazing algorithm was devised to recompense attenuation inconsistency in the propagation path [10]. The residual energy values of various colour channels in background light are used to estimate the water depth, based on this colour compensation is performed to restore colour balance.

A. S. A. Ghani et al. utilised modified Von Kries hypothesis for contrast correction and Rayleigh distribution is employed to expand the image into two distinct intensity images [11]. Subsequently, colour correction is conducted within the hue-saturation-value (HSV) colour model. Nevertheless, the presence of blue-green illumination hinders the contrast enhancement, resulting in a lack of clear differentiation between objects and the background. X. Fu et al. developed a three-stage enhancement method, in which, initially, colour correction was carried out [12]. Secondly, a new retinex framework was developed to decompose reflectance and illumination components. In the third stage, these components are treated properly to avoid under-exposure and fuzz in the images to obtain enhanced image.

C. Li and J. Guo explored dehazing and colour correction algorithms are explored for UIE, where initially, TM is estimated to perform dehazing [13]. The normalized residual energy values for various colour channels are recompensed exponentially. Further, histogram equalization and denoising are performed to enhance the UIM. Y. Wang et al. developed a fusion strategy to fuse images after colour correction and contrast improvement in the frequency domain [14]. Wavelet decomposition is applied at three levels to represent various frequency components of these images. The enhanced image is derived by fusing the low frequency component using a biased average and the superior frequency component using local variance.

C. O. Ancuti et al. technique entails blending of colour-corrected and WB of the original degraded image [15]. This technique does not involve any prior knowledge of the underwater scene or habitat; it only uses a single image. WB image is processed with gamma correction and sharpening before performing multi-scale fusion. Y. Liu et al. developed method uses fusion-based descattering techniques along with color correction to achieve UIE for deep-sea images [16]. Initially, colour deviation was corrected by frequency-based colour estimation. In second phase, lingering low contrast and colour-shift at pixel level are addressed by descattering. This method was tested rigorously on datasets and real-time images of various depths and illumination levels.

Y. Ueki and M. Ikehara developed UIM using a generalization of the dark channel prior (GDCP) has been developed [17]. This method combines output from an iteration of GDCP with image fusion. This method majorly concentrated on UIM with depth as existing algorithms have failed to address. W. Zhang et al. devised a new method for UIE with colour correction and contrast enhancement was achieved using bi-interval histogram equalization [18]. Frequency components are filtered by applying a Gaussian low-pass filter, and subsequently, an exploration into a linear fusion mechanism is undertaken to combine the improved high- and low-frequency components. Y. E. Tao et al. implemented underwater image enhancement through a two-step strategy [19]. Optimal colour compensation was carried out to achieve white balancing; further white balanced image is fused with an artificial underexposure image which is obtained by the gamma-correction process.

Y. Zhang et al. utilized WB and DCP to compensate for colour variation and to increase the contrast of the UIM respectively [20]. Additionally, the images after color-correction and contrast-improvement are fused at multiple scales to yield an enhanced image. Multi-scale is achieved through Gaussian and Laplacian pyramids. C. Dai et al. devised a hybrid UIM processing approach comprising of IReM and colour colour-balancing algorithm has been devised [21]. A new scoring method was introduced to precisely localize background regions. The Transmission Map (TM) is computed through the decomposition of the attenuation curves within the RGB channels. It made this approach to restore UIM effectively. IReM requires a degradation model and it has been combined with IEnM to make the method a hybrid technqiue to enhance the UIM effectively.

Guo et al. introduced a CNN model to separate underwater lighting effects from degraded images, using a light transfer method to estimate illumination and reflectance images [22]. This method achieved state-of-the-art performance on public datasets such as UIEB and EUVP but struggled to produce truly clear underwater images. Li et al. introduced an UIM method based on medium transmission-guided multi-color space embedding, addressing challenges like color distortion, low contrast, and haze. Its strengths lie in effectively restoring visual quality and preserving natural colors through innovative use of color spaces and medium transmission modelling. However, it has limitations such as high computational cost, reliance on specific degradation assumptions, and reduced performance in extreme cases of turbidity or lighting variations, potentially affecting scalability for real-time applications [23].

Iqbal et al. devised a Laplace decomposition-based enhancement technique to tackle issues like reduced contrast and color distortion [24]. Strengths include its computational efficiency and ability to enhance visibility by decomposing images into frequency components for targeted processing. Combining these components produces enhanced images with improved contrast, color correction, edge preservation, and reduced artifacts.

However, limitations include challenges in handling complex lighting conditions and potential over-enhancement in highly degraded images, which may lead to unnatural visual results. Pei and Chen designed an underwater dehazing model focusing on haze removal, color correction, and detail enhancement, achieving superior visibility and effectively eliminating water color distortions [25)].

Xue et al. presented a multi-stage algorithm combining color correction, contrast enhancement, multi-scale fusion, and multi-scale decomposition to address blue-green bias, improve visual effects [20)], [26)], and enhance image details. However, the method's stability in feature matching was limited. Pang et al. implemented a UIM model using contrast-limited histogram equalization for local contrast correction, effectively recovering image structure and statistical characteristics while enhancing global contrast [27)].

Narla et al. introduced a hybrid approach combining physical and learning-based enhancement to balance data-driven semantic transfer and scene-relevant reconstruction [28)]. This method significantly improves visual quality and supports high-level visual tasks. Ouyang et al. addressed issues of color distortion and low contrast leveraging balanced adaptation compensation [29)]. The methodology involves compensating for underwater attenuation and adaptively balancing color and brightness. The method has reduced performance in extremely turbid environments and potential reliance on pre-defined parameters, which may limit flexibility in highly variable underwater conditions.

Rao et al. developed a deep learning-based color compensation method for generalized underwater image enhancement, leveraging a neural network trained on diverse underwater datasets to correct color distortion and improve visibility [30)]. The methodology integrates deep feature extraction with color compensation for robust enhancement across varying underwater conditions. However, limitations involve high computational demands and dependence on training data, which may limit generalization to unrepresented conditions or real-time applications.

A single method is not sufficient to enhance the UIM which suffers from non-uniform illumination, colour cast, noise and blur. Hence, a few multistep methods came into the picture and these outputs are fused using a fusion strategy. The proposed method is strongly motivated by insights from the reviewed literature on underwater image enhancement, addressing key challenges such as inadequate color correction, limited contrast enhancement, and ineffective haze removal. Existing techniques, like fusion-based approaches ([9)], [15)]), often fail to integrate these enhancements cohesively, while methods such as Retinex ([12)]) or intrinsic image-based enhancement ([22)]) excel in specific areas but lack comprehensive solutions. To overcome these limitations, the proposed method employs white balancing (WB) for color correction, contrast-limited adaptive histogram equalization (CLAHE) for contrast enhancement, and dark channel prior (DCP) for haze removal. Notably, applying DCP after WB on color-corrected images improves haze elimination, addressing limitations seen in prior works ([10)], [17)]). Additionally, the adoption of a multi-scale fusion strategy integrates the pre-processed inputs (color-corrected and contrast-enhanced images), ensuring balanced enhancement of global structure and local details. This approach not only improves clarity and visual quality across diverse underwater conditions but also outperforms conventional fusion strategies ([9)], [14)]) by addressing blurred details and achieving superior adaptability, making it a robust solution for underwater image enhancement.

With this motivation, in the proposed method, WB, CLAHE and DCP are used to obtain colour-corrected, contrast-enhanced, and de-hazy images respectively. These processed UIMs are combined using a multi-scale fusion strategy. This work's primary contributions include:

- DCP is explored to eliminate the blurred details. This has been carried out after white balancing i.e. on colour-corrected images which improved the performance of DCP.
- A fusion strategy has been adopted to combine colour-corrected UIM with contrast-enhanced UIM at multi-scale.

The paper's remaining sections are organized as follows: Section 2 provides a comprehensive framework of proposed UIE method, including the fusion strategy. Section 3 deliberates the experimental setup and validation of the present developed UIE method, along with the outcomes. In Section 4, conclusions and the future scope of the proposed method are presented.

2. Proposed Methodology

Underwater image enhancement is accomplished through the fusion of 2 images obtained from DCP and CLAHE after white balancing. The stages of the proposed method are described below and are shown in Figure 1.

- Begin with the input image to be enhanced.
- Apply a white-balancing algorithm to the input image.
- Enhance contrast by implementing CLAHE on the white-balanced image.
- Utilize the DCP operation on the white-balanced image to eliminate haziness.
- Fuse the contrast-enhanced image and dehazed image at multiple scales to produce an enhanced image.

2.1. WB algorithm for pre-processing

The goal of white balancing (WB) is to provide color

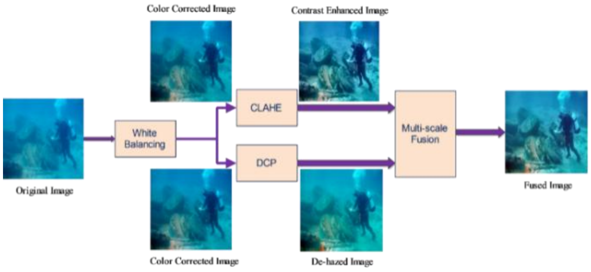

Fig. 1: Process flow of proposed method

constancy or to help preserve color balance so that the final output image is compatible with the Human Visual System (HVS). The original UIM is represented by I and the colour-corrected underwater image I_{out} is achieved through the following process.

$$\mu = g_1 . \left(\frac{\mu_I}{\mu_{ref}}\right) + g_2 \quad (1)$$

$$I_{out} = \frac{I}{\mu} \quad (2)$$

where $\mu_I = (\mu_R, \mu_G, \mu_B)$ represents the totality of the average of individual colour channels. μ_{ref} is the average of the scene. g_1 is the RGB gain factor calculated by extreme value of R, G, B channels individually. g_2 value varies from [0, 0.5] and for acquiring the better results, the default value is fixed at 0.2. The luminosity of white balanced image gets increased when g_2 approaches to zero.

WB algorithm pre-processes UIM and produces a colour corrected image. However, there's still a lot of haziness and poor contrast inherent in this pre-processed underwater image. The overall visibility of UIM has not been enhanced. Therefore, this pre-processed image is further treated with CLAHE and DCP to generate two images.

2.2. CLAHE

CLAHE is an adaptation of the traditional histogram equalization technique [31]. It is well-suited for larger image regions because background noise can introduce peaks that impact the enhancement. When the grey level range is limited, minor contrast variations can be lost during this process. Therefore, CLAHE is employed to achieve optimal contrast enhancement, making it a commonly used method in underwater image enhancement (UIE) for achieving optimal contrast improvement.

In CLAHE, the histogram must be clipped at a predetermined value to calculate the cumulative distribution function. This clipping is necessary to limit the amplification. CLAHE operates on small image regions, often referred to as partitions, blocks, or tiles. For each related partition, CLAHE applies histogram equalization. Two primary parameters, namely the tile size and clip limit, have a major impact on regulating the improved image's quality. An increase in the clip limit leads to a reduction in image intensity, while a decrease enhances it. Similarly, if the tile size is increased, the dynamic range also increases, and vice versa. The equalized distribution of grey values in the image results in improved visibility of hidden properties within the image.

In this method, L*a*b* colour space is chosen for the luminance enhancement of the image. CLAHE can be applied on individual components of colour model. For the L* value, 0 indicates black and 100 indicates white. The a* axis represents the green–red opponent colour. The $b*$ axis denotes the blue–yellow opponents.

Since the L*a*b* is a device-independent colour space, in our approach CLAHE is operated on this colour space as it is 3-D and maps to the range of human colour perception. Here, firstly the pre-processed image which is in the RGB colour space is transformed to the CIELAB colour model. Next, the Luminance channel (L*) in Lab colour model (L*a*b*) is separated and the values of L* are scaled to the range [0, 1]. Then the CLAHE on the Luminance channel is applied, setting the tile size to 8*8 and the clip limit to 0.005. The result is scaled to fit into the range of the L*a*b* colour space. Finally, the resultant image is transformed back into the RGB colour model. By this way, the image contrast is effectively improved by CLAHE.

2.3. DCP

In the proposed method, DCP algorithm is applied to the CLAHE output for contrast improvement. The implementation steps involved in the DCP dehazing algorithm are given below:

$$J^{dark}(x) = min_{y \epsilon \Omega(x)}(min_{c \in \{r,g,b\}} J^c(y)) \quad (3)$$

where $J^c(y)$ is a colour channel, $min_{y \epsilon \Omega(x)}$ is a minimum filter, $min_{c \in \{r,g,b\}}$ is the least value of the R, G, B.

i) Framing the UIM hazy model

The hazy UIM can be well described by the below equation.

$$I(x) = J(x).t(x) + B.(1 - t(x)) \quad (4)$$

where *I(x)* denotes the "Hazy UIM", *J(x)* denotes the "Haze-reduced UIM", *t(x)* denotes the "Transmission map", *B* denotes the "Background colour of the water body".

ii) Estimation of the Background colour of the waterbody

In the DCP method, the hazy images tend to have more brightness in its dark channel. Among those brightest pixels, the maximum intensity pixels in the hazy UIM i.e., input 1 are selected as Background colour estimate (*B*) of the waterbody. It is a vector of size three containing r, g, and b content.

iii) Estimation of the TM

TM t(x) is obtained by applying a dark channel on the normalized hazy underwater image and can be computed as:

$$t(x) = 1 - \left(\omega \times J^{dark}\left(\frac{I_c(y)}{B_c}\right)\right) \quad (5)$$

where J^{dark} is the Dark channel, $\frac{I_c(y)}{B_c}$ is the normalized hazy UIM and $\omega = 0.95$. The estimated transmission map is refined further as in [8].

iv) Restoration of the underwater Haze-reduced image

The restored underwater haze reduced image is calculated from Eq 6.

$$J(x) = \frac{I(x) - B}{max(\ t(x), t_0\ )} + B \quad (6)$$

where t_0 is used to limit the transmittance from being too small.

2.4. Multi-Scale fusion

Image fusion is the technique which allows perceiving more information from a fused image than from a single image. In the processing of satellite images, it has been frequently used. In the proposed strategy, the fusion is deployed at multiple scales instead of single scale as multi-scale fusion avoids image blending artifacts [17]. For the two inputs, the Laplacian pyramid, the Gaussian pyramids are obtained and are operated over the normalized weight maps. The Gaussian pyramid is simply a repeated blurring and downscaling. The Laplacian pyramid is obtained by the difference of Gaussian pyramid levels. Both these pyramids are considered with equal number of levels i.e., five levels. At each level, blending is performed between the two pyramids and summed up subsequently which finally results in the fused output.

Weight maps are the image features extracted from the input images. "Global contrast (W_G)", "Local contrast (W_L)", "Saliency (W_S)" and "Exposedness (W_E)" are the four different weight maps used in this context [17]. The extracted weight maps are summed up as "W_1", "W_2" and further normalized separately as "$\overline{W_1}$", "$\overline{W_2}$".

$$W_1 = W_G^1 + W_L^1 + W_S^1 + W_E^1 \quad (7)$$

$$W_2 = W_G^2 + W_L^2 + W_S^2 + W_E^2 \quad (8)$$

$$\overline{W_1} = \frac{W_1}{W_1 + W_2} \quad (9)$$

$$\overline{W_2} = \frac{W_2}{W_1 + W_2} \quad (10)$$

$$J_l = \sum_{k=1}^{2} G_l\{\overline{W_k}\} \times L_l\{I_k\} \quad (11)$$

where $\overline{W_k}$ represents the "Normalized weight map", I_k represents the "Input images", l denotes the "Number of levels present in the pyramids", $G_l\{\overline{W_k}\}$ and $L_l\{I_k\}$ *represents* the "Gaussian and Laplacian versions of the normalized weight maps and input images" respectively. The summation of all fusion contributions of the inputs results in the enhanced image which contains more information than the individual input images.

3. Experimentation and Discussion

The developed method is validated through experimentation carried out with Matlab 2021 on CPU with i5 processor, 8GB RAM, 2.3 GHz. The method has been tested on three datasets viz., U45, RUIE, UIEB. The initial set of experiments concentrates on a qualitative analysis of our developed method. Subsequently, the credibility of the developed technique is quantitatively demonstrated. Finally, a comparative analysis of the developed method with existing methods is provided.

3.1. Dataset

The proposed method has been assessed using three datasets, namely U45, RUIE [32] and UIEB. U45 dataset consists of 45 images of 256X256 dimensions in PNG format with different degradations such as colour casts, poor contrast and haziness. RUIE dataset consists of 4230 images categorized into three subsets which can cater to the challenging scenarios of enhancement. A set of 400 images are considered from these categories for experimentation. UIE Benchmark is a real-world data set of 890 underwater images including reference images. Another set of 60 UIM which does not have reference is considered as challenging data.

3.2. Performance metrics

The datasets U45 and RUIE do not provide reference images, whereas UIEB does contain reference images. As a result, the evaluation of the developed method involves the use of both full reference (FR) and no reference (NR) metrics. In the case of U45 and RUIE, the input image is regarded as the reference when calculating FR metrics as described below. This approach allows us to estimate the performance of the developed method in both scenarios.

MSE: Mean Square Error

$$MSE = \frac{1}{N}\sum_{p=1}^{N}(Im(p) - RIm(p))^2 \quad (12)$$

Where $Im(p)$ and $RIm(p)$ are pixel intensities of image to evaluate and ground truth or reference image respectively.

PSNR: Peak Signal to Noise Ratio

$$PSNR = 10\ log_{10}\left(\frac{I_{max}^2}{MSE}\right) \quad (13)$$

Where I_{max} is highest pixel intensity in the image. Entropy measures the randomness in image texture.

$$E = -\sum_{i=1}^{N} P_i log_2 P_i \tag{14}$$

Where P_i is the likelihood of occurrence of i^{th} intensity and N is the pixels count.

UIQM

The Underwater Image Quality Measure (UIQM) metric is composed of three individual quality measures specific to underwater images: UIM colourfulness (UICM), UIM sharpness (UISM), and UIM contrast (UIConM). According to the characteristics of the HVS, each of these parameters has been chosen to evaluate a specific area of UIM degradation. A higher UIQM score denotes better image quality because it shows a result that more closely matches human visual perception.

$$UIQM = C_1 \cdot UICM + C_2 \cdot UISM + C_3 \cdot UIConM \tag{15}$$

where $C_1 = 0.0282$, $C_2 = 0.2953$, $C_3 = 3.5753$

UCIQE

UCIQE metric is a direct amalgamation of contrast, saturation, and chroma. It is utilized to assess the varying color cast, blurriness, and low contrast that are characteristic of UIM. The UCIQE is given as:

$$UCIQE = K_1 \cdot \sigma_c + K_2 \cdot con_l + K_3 \cdot \tag{16}$$

where $K_1 = 0.4680$, $K_2 = 0.2745$, $K_3 = 0.2576$, σ_c is ‘standard deviation of chroma’, con_l is ‘contrast of luminance’ and μ_s is ‘average of saturation’. A better image's color vibrancy and contrast are suggested by a greater UCIQE value, which shows an improved of chroma, saturation, and contrast.

3.3. Qualitative analysis

The developed method consists of four stages and the output of each stage is presented qualitatively. The visual results on U45, RUIE and UIEB are demonstrated in Figure 2, Figure 3, and Figure 4 respectively. It is evident that WB performed colour correction, CLAHE improved contrast and DCP reduced haziness in the image. Multi-scale fusion steered the combination of colour corrected and de-hazed image with improved contrast.

3.4. Quantitative analysis

The developed method is evaluated quantitatively on three datasets with full reference and no reference metrics. Generally, two no-reference metrics UIQM and UCIQE are used in state-of-art to evaluate the underwater image quality. MSE, PSNR, SSIM, and entropy are regarded as full reference metrics, while two no-reference metrics are also included in the evaluation.

The proposed underwater image enhancement method demonstrates varied performance across the three benchmark datasets (U45, RUIE, and UIEB), reflecting its ability to address diverse underwater imaging challenges.

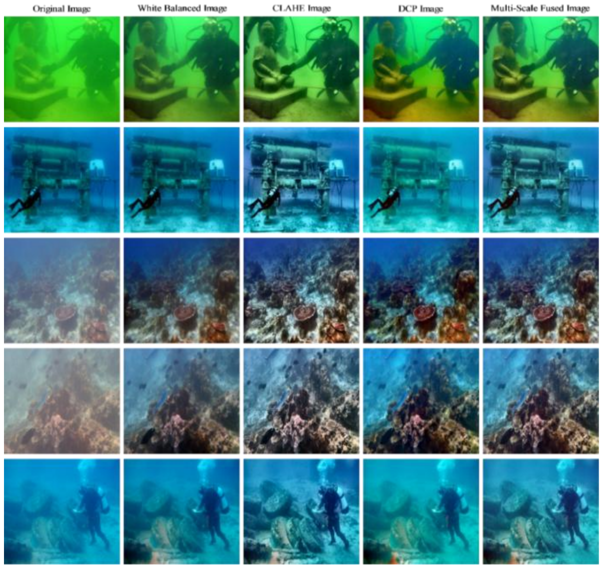

Fig. 2: Qualitative performance on U45

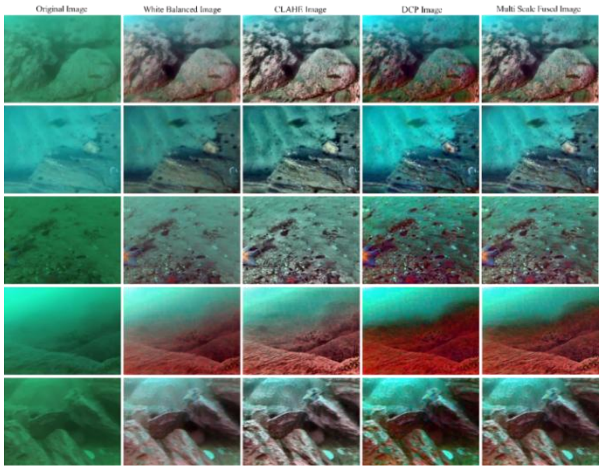

Fig. 3: Qualitative performance on RUIE

It achieves the best PSNR (22.4200) and SSIM (0.8527) on the UIEB dataset, indicating its effectiveness in preserving structural details and visual quality for relatively less complex underwater images. Additionally, the U45 dataset shows the highest UISM (7.3367) and UIQM (3.8097), highlighting the method’s strong capabilities in enhancing sharpness and perceptual qualities such as contrast and color balance. However, the RUIE dataset exhibits lower scores in SSIM (0.7260) and UISM (5.0126), suggesting that the method may face challenges in handling more intricate underwater scenarios, such as highly degraded images. Performance metrics reveal that it can provide colour correction, enhance contrast and reduce haziness. Therefore, it is apparent that our developed technique performs well on three benchmark datasets.

Despite its strengths, there are areas for improvement. The UICM values remain highly negative, suggesting persistent biases in underwater color correction, particularly for datasets like U45 and RUIE.

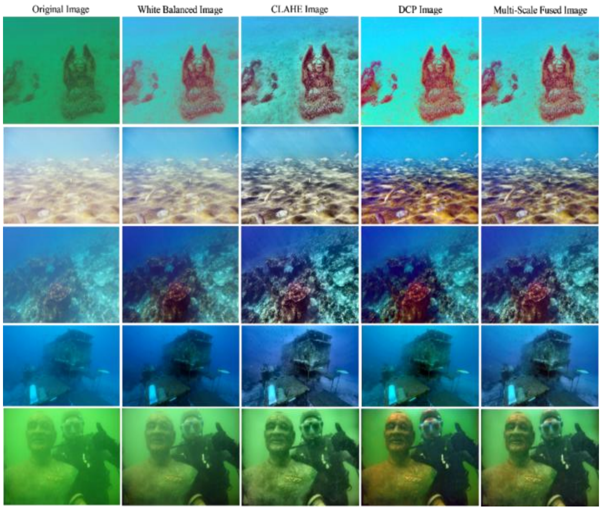

Fig. 4: Qualitative performance on UIEB

Enhancements in color balance and contrast (UCIQE and UIQM) are also necessary for datasets like UIEB and RUIE to further improve visual quality. Further, performance is analyzed at each stage in the process flow of the developed method and is presented in Tables 1, 2 and 3. It is observed that UIQM and UICQE are improved stage by stage and finally attained satisfactory value for three datasets. The performance of our developed technique is contrasted with other well-known methods in terms of UIQM, UCIQE, SSIM and PSNR. To ensure diversity, a set of 500 images from the three datasets is considered. UCIQE is adopted to measure varying colour cast, blur, and low contrast that portray UIM.

Later, a comparison of the developed technique with the existing techniques is demonstrated in Figure 5 and 6. The supremacy of the developed approach is evident in Figure 5 and 6, as it outperforms other methods in terms of PSNR and SSIM. The recent existing methods such as Joint optimization [33], GAN [34], U-Net [35], MIRNet [36], Multi-Scale fusion 37) are considered for comparative analysis. The PSNR (Peak Signal-to-Noise Ratio) comparison clearly demonstrates the superiority of the proposed method in underwater image enhancement. With a PSNR value of 22.42, it slightly outperforms the Multi-Scale Fusion technique (22.35), which was previously one of the best-performing methods. This indicates that the proposed method effectively reduces noise and improves the visual fidelity of the enhanced images.

In comparison to other methods such as GAN [34] (19.16), U-Net [35] (17.63), MIRNet [36] (17.3), and Joint Optimization [33] (17.29), the proposed method achieves a significant improvement, showcasing its ability to handle the complexities of underwater image degradation. These results highlight the effectiveness of incorporating color correction, contrast enhancement, and multi-scale fusion strategies into the enhancement pipeline. The marginal improvement over Multi-Scale Fusion [37] suggests that the proposed integration of additional steps, such as enhanced dehazing via DCP, successfully builds upon prior advancements. This strong performance establishes the proposed method as a benchmark for future research in underwater image enhancement.

Table 1: Performance of developed method on U45 dataset at different stages

Metric	Original Image	WB Image	CLAHE	DCP	MS Fused Image
MSE	0	1467.15	1234.25	1021.45	434.25
PSNR	65535	16.4661	17.2168	18.0386	21.7534
SSIM	1	0.7721	0.6523	0.6899	0.7856
Entropy	6.4774	6.4774	7.4175	7.0274	7.3515
UICM	-75.462	-53.778	-49.885	-64.147	-49.905
UISM	7.3128	7.2869	7.4028	7.1950	7.3367
UIConM	0.6477	0.7568	0.7209	0.7101	0.8532
UIQM	2.3472	3.3411	3.3568	2.8549	3.8097
UCIQE	0.4814	0.5678	0.6027	0.6032	0.5929

Table 2: Performance of developed method on RUIE dataset at different stages

Metric	Original Image	WB Image	CLAHE	DCP	MS Fused Image
MSE	0	1937.754	1534.25	1255.75	533.18
PSNR	65535	15.2578	16.271	17.1418	20.8621
SSIM	1	0.4913	0.4530	0.4220	0.7260
Entropy	6.2178	6.2178	7.5182	7.3187	7.4319
UICM	-82.355	-32.572	-32.463	-38.028	-30.992
UISM	2.4395	2.9596	5.6022	4.3074	5.0126
UIConM	0.5633	0.7005	0.8207	0.7624	0.8544
UIQM	0.4120	2.4600	3.6734	2.9254	3.6611
UCIQE	0.4154	0.5475	0.5742	0.6094	0.5837

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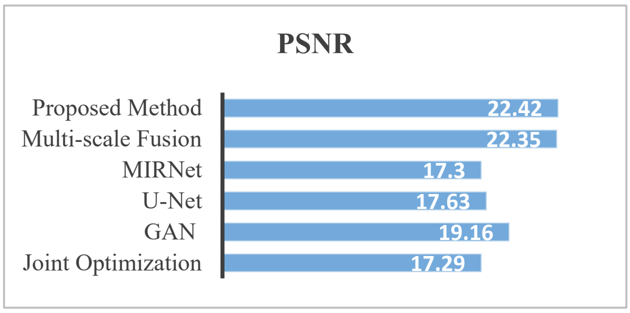

Fig. 5: Comparative Performance of the developed approach based on PSNR

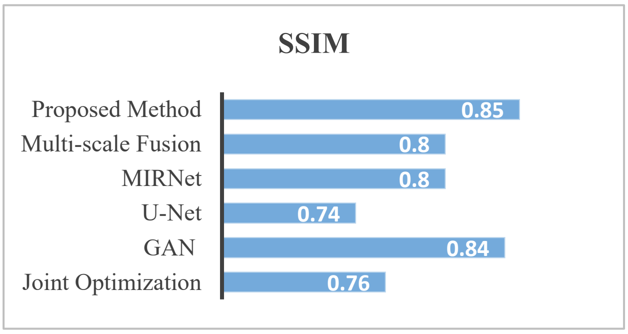

Fig. 6: Comparative Performance of the developed approach based on SSIM

4. Conclusion

A hybrid approach of UIE has been developed by utilizing DCP with WB and CLAHE. Initially, CLAHE is applied on white balanced image. DCP is also applied on white balanced image to remove haziness. Finally, CLAHE output and DCP output are fused by considering different weight maps to obtain the enhanced UIM. Experimentation has been carried out on U45, RUIE and UIEB datasets. The proposed method was evaluated qualitatively to show that enhanced image is a colour corrected, contrast improved and de-hazy image. Quantitative analysis in terms of UIQM and UICQE demonstrated that the proposed technique is able to offer superior performance against distorted and hazy images. As a result, this experimentation has demonstrated that the developed work outperforms the existing methods. Future research can explore advanced fusion strategies, multi-color space embeddings, and hybrid approaches that combine physical and learning-based methods to better generalize across diverse underwater conditions. Additionally, focusing on edge preservation and structural detail enhancement can address limitations observed in datasets with more complex degradation.

Conflicts of Interest

The authors declare no conflict of interest.

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