A Combined Approach of Color Correction and Homomorphic Filtering for Enhancing Underwater Images

Ahila Priyadharshini R[1], Ramajeyam K [2]

Dept.of ECE [1, 2,]
Mepco Schlenk Engineering College, Sivakasi
[1]rahila@mepcoeng.ac.in, [2]ramjeyam1199@gmail.com

Abstract Underwater imaging is crucial for marine biology, oceanography, and underwater archaeology, but low-quality images often result from issues like speckle noise, backscatter noise, and blur. To address the difficulties posed by these challenges, a recent study presents an effective methodology for enhancing the visual quality of underwater images. The approach comprises color correction, contrast enhancement, homomorphic filtering, and fusion. Contrast Stretching is also used to improve contrast based on the range of intensity values. The proposed method is evaluated through qualitative and quantitative assessments, demonstrating its effectiveness in improving image details, enhancing global contrast, and exposing dark areas. According to the results, the proposed methodology surpasses several state-of-the-art techniques currently in use. The ultimate objective is to enhance the visual quality of underwater images, and the outcome of the study is a strong methodology that effectively tackles the challenges of underwater imaging, leading to improved image quality.

Keywords: Underwater Images, White Balancing, Contrast Enhancement, Homomorphic Filtering, Fusion, Contrast Stretching

1 Introduction

In recent years, the image processing and underwater vision fields have placed significant emphasis on enhancing the quality of underwater images. Both areas have recognized the importance of enhancing the clarity and visual representation of underwater imagery [1]. The development of underwater imaging systems for military drones [2], as well as the growing interest from the commercial and consumer sectors, have led to increased accessibility and exposure in various marketplaces [3]. However, there are fundamental constraints imposed by the underwater environment, which presently limit the quality of these images. The presence of speckle noise, backscatter noise, color distortion, motion blur, low visibility, and low contrast degrades the overall quality of the image [4]. These factors arise from the optical process of forming underwater images, which is distinct from that of imaging in the air due to light scattering in the underwater medium. Despite these challenges, it is essential to avoid over-enhancing and saturating underwater images. Fig1 presents a collection of underwater images that exhibit different types of degradation.

Fig.1 Examples of underwater images with different degradations

According to the Jaffe-McGlamery model, which is depicted in Figure 2 and referenced in [5] an underwater image can be divided into three parts: L_d, L_f, and L_b. L_d represents the direct reflection from the object, which is not scattered by the water, while L_f refers to the forward scattering light reflected by the object at a small angle, and L_b is the backscattered light that enters the camera without reflecting off the object. Since underwater images are affected by complex imaging models and poor lighting conditions that can degrade their visual quality, enhancing their quality is essential to convert low-quality images into high-quality ones. Equation (1), which corresponds to Jaffe-McGlamery's model, can be used to decompose an underwater image into its components, thereby aiding in the understanding and improvement of the image's quality.

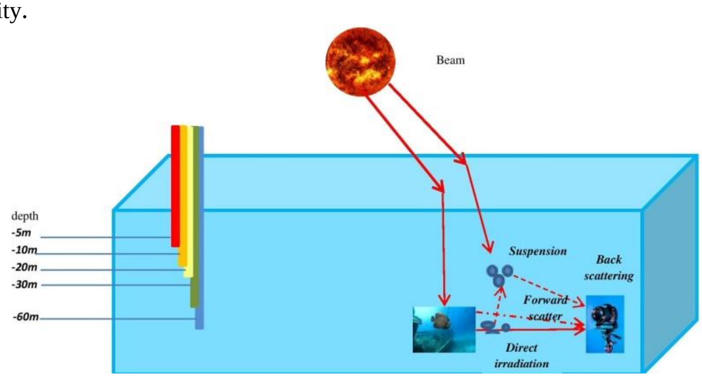


Figure 2 - Jaffe-Mcglamery’s Model [5]

$$L_I = L_d + L_f + L_b \quad (1)$$

Researchers have extensively explored methods to enhance the clarity of underwater images by addressing the haziness present in them. Chongyi Li et al [6] introduced a method that utilizes smearing and color correction algorithms to tackle color and contrast challenges in underwater images. To counteract the noise resulting from the physical characteristics of the underwater medium, they employed a histogram equalization algorithm and bilateral filtering for enhancing contrast and correcting colors. In their study, Wang et al [7] introduced a method for enhancing low-light underwater images. Their methodology involved obtaining a haze-free image, followed by enhancing the contrast, brightness, and overall visual quality through various techniques such as Histogram Equalization, color correction, and stretching of the HSI model. Priyadharshini and Aruna [8] proposed an effective technique for enhancing visibility in hazy conditions to prevent road image degradation. Their approach removes haze without introducing noise or artifacts, making it suitable for applications like autonomous driving and surveillance systems. De Vleeschouwer et al [9] developed an algorithm that utilizes a fusion approach with two inputs, namely, a color-corrected image and an image with improved contrast. The algorithm estimates these inputs to enhance the overall quality of the underwater image. Khan et al [10] employed a wavelet-based fusion method in their investigation to address the color and contrast issues often encountered in underwater imagery. They incorporated techniques such as histogram stretching and CLAHE to enhance the contrast and rectify the color distortion that occurs due to low-contrast and color attenuation typical in hazy images. As a result, their approach proved effective in enhancing the overall quality of underwater images. In their research, Cosmin et al [11] presented a method to address the difficulties posed by underwater conditions, where they produced two inputs showing a color-corrected and contrast-enhanced rendition of the initial underwater image. This technique combines the two inputs to mitigate the presence of halos and color distortions, thus leading to a refined image with reduced noise and enhanced visibility. Jiang et al [12] put forward a novel approach to address the issue of degraded underwater images, which involves using a target-oriented perceptual adversarial network that incorporates an adaptive fusion of latent aspects. This technique is designed to effectively remove degradation in underwater images while prioritizing the preservation of specific target features. Wang, X. Ding et al [13] introduced an approach to improve underwater images using wavelet decomposition and multi-scale fusion. Since water's suspended particles can affect the image quality and accuracy, color correction becomes necessary in the image processing domain. Zuiderveld et al [14] have proposed a contrast limited adaptive histogram equalization (CLAHE) method as an alternative approach for image enhancement. CLAHE balances the target areas by merging the histograms of adjacent regions. As this method works based on the neighborhood regions rather than the whole image, it can effectively deal with non-uniform lighting, leaving the processed image with balanced illumination. In their research, Iqbal et al [15] presented an unsupervised methodology for improving the quality of low-quality images using color correction. The proposed approach utilizes color-balancing contrast correction for the RGB color model, as well as contrast correction for the HIS color model.

Khan et al [16] introduced bi-histogram equalization methods for improving the contrast of digital images while preserving their natural appearance. While multi-histogram equalization methods can maintain image brightness and authenticity, they may sacrifice either contrast or brightness. However, these methods are more appropriate for images with sufficient lighting and may introduce halo and color distortions in images with poor lighting conditions. The researchers addressed this limitation by enhancing the image results through the elimination of poor lighting conditions.

The aim of this research is to enhance the quality of images taken underwater, and various techniques are available for achieving this goal, each with its own strengths and weaknesses. Existing advanced techniques rely on color correction and multi-image processing, but these methods have downsides such as longer processing times, reduced image contrast, and lower accuracy of restoration. To address these issues, a need for a new and effective approach to underwater imaging has been identified. A novel procedure has been developed for removing the haze that commonly appears in conventional camera underwater images. The essential steps of this proposed methodology are outlined below.

- To improve the quality of the reconstructed image, three algorithms - sharpening, homomorphic filtering, and gamma correction are used to create three variants of the original image.
- The three improved versions of the original image are then merged using a fusion technique that follows a maximum selection rule.
- The maximum selection rule selects the pixel with the highest intensity value from each corresponding input image to form the output image.
- After the fusion process, a contrast stretching algorithm is used to balance the dominant colors in the resulting image.
- The contrast stretching algorithm enhances the overall quality of the image.

2 Materials and Methods

The preceding section provided an overview of various studies conducted in the domain of underwater imaging. In this work, we have approached a new technique which utilizes a three stage methodology to improve the quality of underwater images. This approach integrates white balance and image fusion techniques to produce superior quality images. The framework's design is depicted in Fig 4, which illustrates the different stages involved in the proposed strategy.

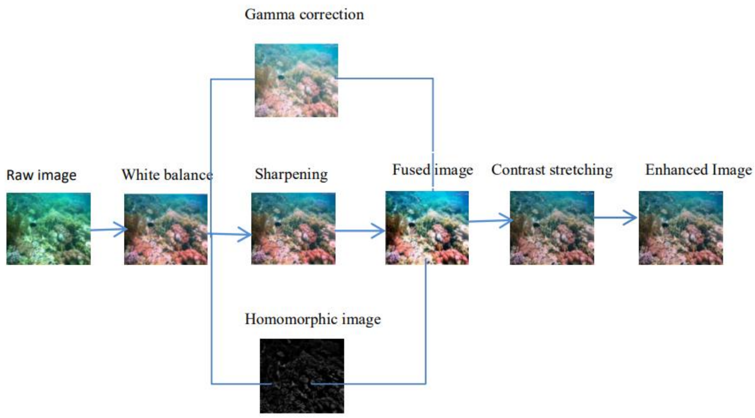


Fig 4. Block diagram of Proposed enhancement technique

2.1 Color balancing

2.1.1 White balancing

White balancing [17] is a useful technique for eliminating undesired color casts from an image. This is especially important for underwater photography, where light scattering can cause color distortion. To achieve a natural look in underwater images, white balancing is typically applied to the three primary colors. However, in this environment, only the green color tends to be accurately preserved. As a result, to perform white balancing on underwater images, it is necessary to extract the red and blue channels using the green channel at each pixel location, applying equation (2) and (3), and ensuring that the resulting normalized image rate falls within the range of 0 to 1

1) For red color, I_{rc} at each pixel location (x)

$$I_{rc}(x) = I_r(x) + \alpha\,[\overline{I_g} - \overline{I_r}][1 - I_r(x)]\,.\; I_g(x) \tag{2}$$

2) For blue channel, I_{bc} at each pixel location (x)

$$I_{bc}(x) = I_b(x) + \alpha\,[\overline{I_g} - \overline{I_b}][1 - I_b(x)\,]\,.\; I_g(x) \tag{3}$$

2.1.2 Gamma correction

Gamma correction [17] is a method used to adjust the contrast of an image between its dark and bright areas. This correction tends to reduce the contrast in underexposed regions while enhancing the darker areas of the image. By adjusting the luminance or brightness of an image, gamma correction aims to make it more consistent with the way the human eye perceives brightness [17]. This technique involves applying a specific function that maps the image's luminance levels to compensate for the non-linear luminance effect that result from displaying an image on a screen.

2.1.3 Sharpening

In [17], the technique of normalized unsharp masking for image sharpening is explained. This method involves blending a blurred or unsharp version of an image with its original version to enhance its sharpness. The standard unsharp masking formula is utilized, which involves adding a certain parameter (denoted by β) multiplied by the difference between the original image and its Gaussian-filtered version. The sharpened image $I_s$is obtained as$I_s = I_{in} + \beta(I_{in} - G * I_{in})$, where I_{in} is the image that needs sharpening (in this case, the white-balanced image), $G * I_{in}$ represents the Gaussian-filtered version of the imageI_{in}, and β is the parameter that needs to be determined. However, selecting an appropriate value for β is not an easy task. If β is too small, the sharpening will be ineffective, while if it is too large, the image may have excessively bright highlights and dark shadows, leading to oversaturated regions. To address this issue the sharpened image S is defined as follows:

$$S = (I + N\,\{I - G * I\})\,/2 \tag{4}$$

Here, N signifies the linear normalizing operator, commonly known as histogram stretching [17]. This method has the advantage of not requiring parameter adjustments and appears to be effective in terms of image sharpening.

2.2 Homomorphic Filter (HF)

The homomorphic filter [18] is designed on the basis of the assumption that an image can be modeled as a combination of two distinct components: an illumination component and a reflectance component. By applying the homomorphic filter, the illumination component is enhanced, while the reflectance component is attenuated, which ultimately leads to an improvement in image contrast and visibility. To achieve this, the homomorphic filter [18] utilizes a frequency-domain filtering process to separate the two components of the image. The illumination component represents the amount of incident light on the scene [18], while the reflectance component corresponds to the light reflected by the scene. Mathematically, for a given image m(x,y) at a pixel location (x,y), the illumination component I(x,y) and the reflectance component R(x,y) are represented as shown in equation [4].

$$\mathrm{m(x,y) = I(x,y) \times R(x,y)} \tag{5}$$

In order to convert the image from the spatial domain to the frequency domain, a transformation function such as the Fourier transform is typically utilized [18]. Prior to this transformation, however, a logarithmic function is applied to Equation (6), which involves changing the product of the illumination and reflectance components to the sum of the logarithmic components. This process is described as follows

$$\mathrm{Z(x,y) = In(m(x,y)) = In\big(I(x,y)\big) + In(R(x,y))} \tag{6}$$

Applying Fourier transform to the equation gives (5)

$$\mathrm{Z(u,v)} = \ F_i\mathrm{(u,v)} + \ F_r\mathrm{(u,v)} \tag{7}$$

A filter function H(x,y) is applied to the Fourier transformed signal, which is then subjected to inverse Fourier transform to obtain the resulting function. An inverse exponential operation is performed on the resulting function to enhance the image.

2.3 Contrast Stretching

The Contrast Stretching technique, as described in reference [19], is used to enhance the contrast of an image by expanding the range of intensity values. This is achieved through the use of a linear scaling function (8) to adjust the pixel values. However, it should be noted that this method is only effective when the minimum and maximum intensity values of the image are different.

$$S = (r - r_{min})\frac{(I_{max} - I_{min})}{(I_{max-}I_{min})} + I_{min} \tag{8}$$

Here r is used to represent the current pixel intensity value. The minimum intensity value in the entire image is denoted byr_{min}, while r_{max} is used to represent the highest intensity value within the image.

2.4 UIEB Dataset

The ‘UIEB dataset (Underwater Image Enhancement Benchmark)’, as described in [20], includes 890 authentic underwater images that have been captured under different lighting conditions. The dataset also includes a corresponding reference image that has better visibility and brightness compared to the original image, and does not contain a color cast, providing a more authentic representation of the scene.

3 Experiments and Discussions

Our approach to enhancing underwater images comprises three distinct steps, which are input processing, white balancing, homomorphic filtering, and color correction, with the final step being image fusion. The fusion technique utilized in our method involved an average pixel-level approach that mitigates the effects of backscattering, ultimately resulting in superior quality images. In the following section, we assess the sensitivity and performance of the fusion technique proposed in this study regarding its ability to handle low-contrast effects. We compare our approach to existing methods such as ‘He et al. [21], Ancuti et al. [22]’, and various underwater dehazing approaches including ‘Drews, Jr. et al, [23], Galdran et al. [24], Emberton et al. [25], and Vleeschouwer [26]’. We conducted an evaluation of ten methods, including our proposed approach, on the UIEB dataset. This publicly available dataset comprises images with various levels of color distortion, low resolution, and fog. Eight images were selected from the dataset's validation set for our validation experiments, which were conducted using several non-reference evaluation metrics, such as UIQM [27] and UCIQE [27], to compare the experimental results

‘Underwater Image Quality Evaluation Metric’

The objective of the underwater image quality evaluation metrics is to analyze and evaluate the processed underwater image [27]. Currently, there are two established methods for evaluating the quality of such images, namely the ‘underwater color image quality evaluation (UCIQE) and underwater image quality metrics (UIQM).’

i) *Underwater Color Image Quality Evaluation (UCIQE)*

In order to evaluate non-uniform color casts, blurring, and noise in underwater monitor images, the UCIQE method presented in equation 9 was utilized. The UCIQE approach involves converting an underwater image from RGB to CIELAB, which is more consistent with the human visual system, allowing for a more accurate measurement of these image quality metrics[27]. A higher UCIQE score suggests greater harmony between Chroma, saturation, and contrast [27].

$$\text{UCIQE} = c_1 \times \sigma_c + c_2 \times con_l + c_3 \times \mu_s \tag{9}$$

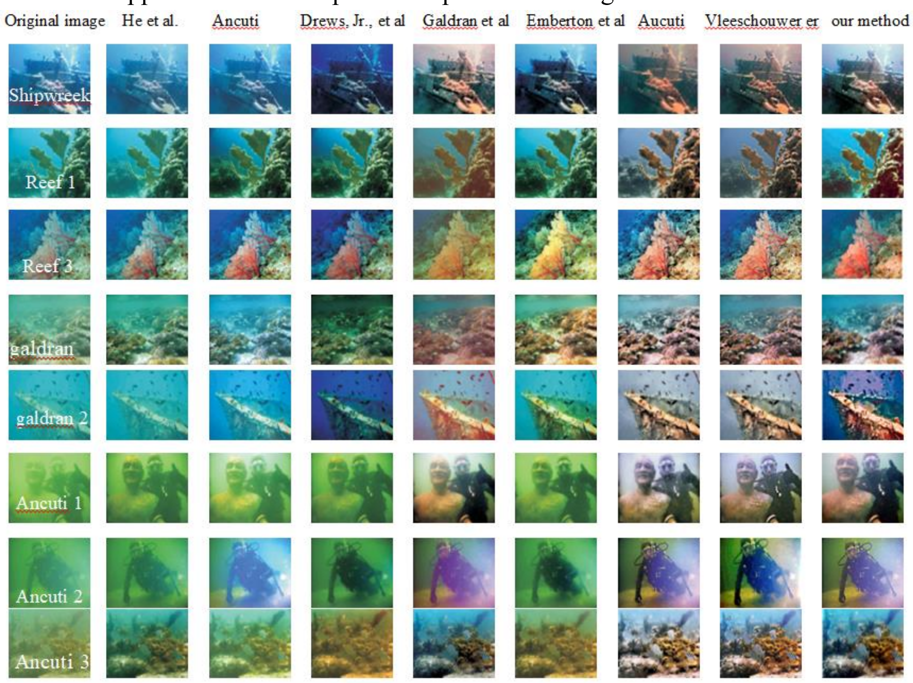
‘Where σ_c is the chroma standard deviation, con_l is the luminance contrast, and μ_s is the average saturation value. These are the weight coefficients: c_1, c_2, and c_3’

ii) *‘Underwater Image Quality Metrics (UIQM)’*

The UIQM is a metric for evaluating the quality of underwater images, which is modeled after the way the human visual system functions [27]. The evaluation of the quality of underwater images is based on three unique metrics: Colorfulness, Sharpness, and Contrast. These measures are specifically tailored to assess the quality of images captured in an underwater environment. A higher score on the UIQM metric indicates that the resulting image is more consistent with the human perception of quality [27].The UIQM is based on a model that is designed specifically for underwater images and aims to accurately capture their unique characteristics. This can be expressed as follows:

$$\text{UIQM} = c_1 \times UICM + c_2 \times UISM + c_3 \times UIConM \tag{10}$$

Where $UICM$, $UISM$, and $UIConM$ correspond to the image colorfulness, sharpness, and image contrast measures, respectively and c_1, c_2, c_3 are the weight coefficients. This paper present a comparison of their proposed image enhancement method to several existing approaches for both outdoor and underwater dehazing. The outdoor methods include those developed by "He et al [21] and Ancuti and Ancuti [22], while the underwater methods include those developed by Drews, Jr., et al. [23], Galdran et al [24], Emberton et al [25], Vleeschouwer [26], Ancuti et al [9], and the our's initial underwater approach". The comparison is presented in Fig. 5



"Fig. 5. Comparison to different outdoor (He et al [21] and Ancuti and Ancuti [22]) and underwater dehazing approaches (Drews Jr et al [23], Galdran et al [24], Emberton et al [25], Vleeschouwer [26] Ancuti et al [9] and our initial underwater approach). The quantitative evaluation associated to these images is provided in Table I and II."

The Quantitative evaluations of the different methods are provided in Tables I and II. Based on these evaluations, it is claimed that the proposed method outperforms the existing methods in terms of objective image quality metrics such as UCIQE and UIQM. Additionally, visual comparisons of the results produced by the proposed method and the existing methods are provided, demonstrating that the proposed method is capable of producing clearer and more visually pleasing images. Overall, the comparison suggests that the proposed method is a promising approach for outdoor and underwater image enhancement

The fusion-based strategy outperforms the dehazing algorithms of "Galdran et al [24] and Emberton et al [25]" in recovering visibility in considered scenes. However, according to Table I and II, the proposed strategy has similar or higher UCIQE and UIQM values than these algorithms. The proposed approach also produces good visual quality, with significant improvements in global contrast, color, and architectural features. Compared to the multi-scale methodology provided in [9], the proposed approach is more robust in harsh underwater environments, such as murky sea water and non-uniform artificial illumination. This is supported by Fig. 5, which shows the proposed algorithm producing clearer and brighter results with more obvious color contrast compared to the fusion algorithm in difficult underwater situations.

Table I Comparison of UCIQE metrics in our method with other existing approaches (The best result is in bold)

Sample images	**He et al. [25]**	**Ancuti& Ancuti [26]**	**Drewsjr [23]**	**Galdran et al.[24]**	**Emberton er al. [25]**	**Ancuti et al. [9]**	**Vleeschouwer er al [26]**	**Our method**
Shipwreek	0.565	0.629	0.55	0.646	0.632	0.634	0.632	0.681
Reef 1	0.612	0.657	0.649	0.576	0.66	0.655	0.658	0.6725
Reef 3	0.606	0.661	0.62	0.533	0.678	**0.705**	0.697	0.6528
Galdran 1	0.593	0.631	0.544	0.529	0.652	0.643	0.659	0.6735
Galdran 2	0.426	0.558	0.536	0.596	0.63	0.667	0.633	0.694
Ancuti 1	0.485	0.561	0.499	0.641	0.499	0.588	0.594	0.621
Ancuti 2	0.456	0.595	0.492	0.529	0.529	0.59	0.592	0.6425
Ancuti 3	0.577	0.643	0.535	0.614	0.555	0.652	0.664	0.698

Table II Comparison of UIQM metrics in our method with other existing approaches (The best result is in bold)

Sample images	**He et al. [25]**	**Ancuti& Ancuti [26]**	**Drewsjr [23]**	**Galdran et al.[24]**	**Emberton er al. [25]**	**Ancuti et al. [9]**	**Vleeschouwer er al [27]**	**Our method**

Shipwreek	0.565	0.578	0.492	0.605	0.558	0.629	0.668	0.671
Reef 1	0.592	0.643	0.657	0.565	0.69	0.674	0.687	0.847
Reef 3	0.578	0.667	0.584	0.524	0.677	0.737	0.766	0.865
Galdran 1	0.578	0.601	0.519	0.569	0.664	0.669	0.68	0.832
Galdran 2	0.421	0.481	0.41	0.648	0.577	0.622	0.663	0.852
Ancuti 1	0.353	0.412	0.383	0.458	0.407	0.547	0.507	0.637
Ancuti 2	0.437	0.651	0.344	0.525	0.425	0.683	0.687	0.69
Ancuti 3	0.596	0.616	0.492	0.646	0.563	0.693	0.651	0.807

Finally, the proposed methodology for "underwater image enhancement" has been found to have the highest level of color correction accuracy, with more diverse color intensity than state-of-the-art approaches. This was further confirmed by the discovery of a color cast, which was corrected more accurately by the proposed method than by the other approaches. The proposed method also offers a simplified version of the fusion method that can replace the mean pixel fusion, albeit at the cost of lower image detail quality. In Fig 6, a comparison of the average image quality metrics for a set of underwater images is presented. This comparison was carried out using a proposed method for image fusion, which involves combining three image processing techniques (sharpening, gamma-correction, and homomorphic filtering) with the corresponding pixel averages of images to create a fused image. Overall, the proposed method is effective in addressing various underwater image distortion scenarios.

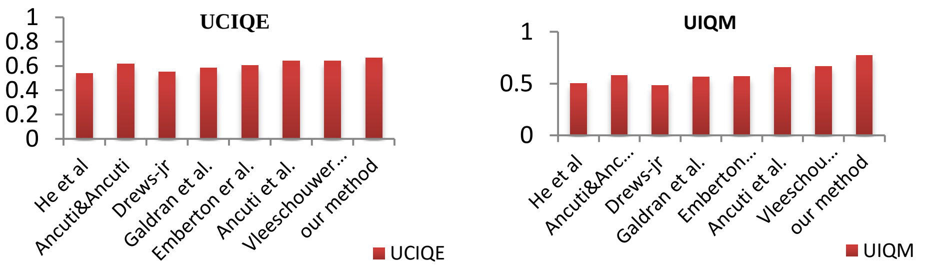


Fig 6 Comparison of average image quality metrics by underwater images

4 Conclusion

This study presents a novel method for improving underwater images by using a fusion principle that follows a maximum selection rule. The proposed method does not require any additional information beyond the original image and effectively enhances various types of underwater images, including those affected by scattering, absorption, noise, haze, low contrast, and color distortion. The method accurately recovers essential faded features and edges, and Figure 5 illustrates how it works.

Our algorithm offers a highly efficient approach to improving the quality of hazy images taken in various underwater environments. Based on the simulation results of UCIQE and UIQM, our fusion approach for improving underwater images outperforms earlier techniques. This technique successfully enhances the image quality while preserving crucial details and edges.

References

1. Jaffe, J. S. (2014). Underwater optical imaging: the past, the present, and the prospects. *IEEE Journal of Oceanic Engineering*, *40*(3), 683-700.
2. Prasath, R., & Kumanan, T. (2020, September). Application of Different Techniques for Underwater Image Processing-A Systematic Review. In *IOP Conference Series: Materials Science and Engineering* (Vol. 925, No. 1, p. 012034). IOP Publishing..
3. Strachan, N. J. C. (1993). Recognition of fish species by colour and shape. *Image and vision computing*, *11*(1), 2-10.
4. Soni, O. K., & Kumare, J. S. (2020, April). A survey on underwater images enhancement techniques. In *2020 IEEE 9th International Conference on Communication Systems and Network Technologies (CSNT)* (pp. 333-338).
5. Jaffe, J. S. (1990). Computer modeling and the design of optimal underwater imaging systems. *IEEE Journal of Oceanic Engineering*, *15*(2), 101-111.
6. Li, C., & Guo, J. (2015). Underwater image enhancement by dehazing and color correction. *Journal of Electronic Imaging*, *24*(3), 033023-033023.
7. Li, C. Y., Guo, J. C., Cong, R. M., Pang, Y. W., & Wang, B. (2016). Underwater image enhancement by dehazing with minimum information loss and histogram distribution prior. *IEEE Transactions on Image Processing*, *25*(12), 5664-5677.
8. R. A. Priyadharshini and S. Aruna,(2018) "Visibility Enhancement Technique for Hazy Scenes," 2018 4th International Conference on Electrical Energy Systems (ICEES), Chennai, India, pp. 540-545, doi: 10.1109/ICEES.2018.8443201.
9. Ancuti, C. O., Ancuti, C., De Vleeschouwer, C., & Bekaert, P. (2017). Color balance and fusion for underwater image enhancement. *IEEE Transactions on image processing*, *27*(1), 379-393.
10. Khan, A., Ali, S. S. A., Malik, A. S., Anwer, A., & Meriaudeau, F. (2016, December). Underwater image enhancement by wavelet based fusion. In *2016 IEEE International Conference on Underwater System Technology: Theory and Applications (USYS)* (pp. 83-88).
11. Ancuti, C., Ancuti, C. O., Haber, T., & Bekaert, P. (2012). Enhancing underwater images and videos by fusion. In *2012 IEEE conference on computer vision and pattern recognition* (pp. 81-88).
12. Jiang, Z., Li, Z., Yang, S., Fan, X. and Liu, R., 2022. Target Oriented Perceptual Adversarial Fusion Network for Underwater Image Enhancement. *IEEE Transactions on Circuits and Systems for Video Technology*.
13. Y. Wang, X. Ding, R. Wang, J. Zhang and X. Fu, "Fusion-based underwater image enhancement by wavelet decomposition," *2017 IEEE International Conference on Industrial Technology (ICIT)*, Toronto, ON, Canada, 2017, pp. 1013-1018, doi: 10.1109/ICIT.2017.7915500.
14. Zuiderveld, K., 1994. Contrast limited adaptive histogram equalization. *Graphics gems*, pp.474-485.
15. K. Iqbal, M. Odetayo, A. James, Rosalina Abdul Salam and Abdullah Zawawi Hj Talib, "Enhancing the low quality images using Unsupervised Colour Correction Method," *2010*

IEEE International Conference on Systems, Man and Cybernetics, Istanbul, Turkey, 2010, pp. 1703-1709, doi: 10.1109/ICSMC.2010.5642311.

16. Farhan Khan, M., Khan, E., & Abbasi, Z. A. (2012). Multi segment histogram equalization for brightness preserving contrast enhancement. In *Advances in Computer Science, Engineering & Applications: Proceedings of the Second International Conference on Computer Science, Engineering and Applications (ICCSEA 2012), May 25-27, 2012, New Delhi, India, Volume 1* (pp. 193-202). Springer Berlin Heidelberg.
17. Tarhate, Saloni, and Richa R. Khandelwal. "Weight Maps Guided Underwater Image Enhancement By Fusion Technique." *Helix* 10, no. 04 (2020): 194-198.
18. Seow, Ming-Jung, and Vijayan K. Asari. "Homomorphic processing system and ratio rule for color image enhancement." In *2004 IEEE International Joint Conference on Neural Networks (IEEE Cat. No. 04CH37541)*, vol. 4, pp. 2507-2511.
19. https://samirkhanal35.medium.com/contrast-stretching-f25e7c4e8e33
20. Li, C., Guo, C., Ren, W., Cong, R., Hou, J., Kwong, S., & Tao, D. (2019). An underwater image enhancement benchmark dataset and beyond. *IEEE Transactions on Image Processing*, *29*, 4376-4389.
21. He, K., Sun, J., & Tang, X. (2010). Single image haze removal using dark channel prior. *IEEE transactions on pattern analysis and machine intelligence*, *33*(12), 2341-2353.
22. Ancuti, C. O., & Ancuti, C. (2013). Single image dehazing by multi-scale fusion. *IEEE Transactions on Image Processing*, *22*(8), 3271-3282.
23. Drews, P., Nascimento, E., Moraes, F., Botelho, S., & Campos, M. (2013). Transmission estimation in underwater single images. In *Proceedings of the IEEE international conference on computer vision workshops* (pp. 825-830).
24. Galdran, A., Pardo, D., Picón, A., & Alvarez-Gila, A. (2015). Automatic red-channel underwater image restoration. *Journal of Visual Communication and Image Representation*, *26*, 132-145.
25. Emberton, Simon, Lars Chittka, and Andrea Cavallaro. "Hierarchical rank-based veiling light estimation for underwater dehazing." (2015).
26. O. Ancuti, C. Ancuti, C. De Vleeschouwer and P. Bekaert, "Color Balance and Fusion for Underwater Image Enhancement," in *IEEE Transactions on Image Processing*, vol. 27, no. 1, pp. 379-393, Jan. 2018, doi: 10.1109/TIP.2017.2759252.
27. Guo, Pengfei, Lang He, Shuangyin Liu, Delu Zeng, and Hantao Liu. "Underwater image quality assessment: Subjective and objective methods." *IEEE Transactions on Multimedia* 24(2021)1980-198