Blending of Contrast Enhancement Techniques for Underwater Images

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Summary
Exploration has always been an instinct of humans, and underwater life is as fascinating as it seems. So, for studying flora and fauna below water, there is a need for high-quality images. However, the underwater images tend to be of impaired quality due to various factors, which calls for improved and enhanced underwater images. There are various Histogram Equalization (HE) based techniques which could aid in solving these issues. Classifying the HE methods broadly, there is Global Histogram Equalization (GHE), Mean Brightness Preserving HE (MBPHE), Bin Modified HE (BMHE), and Local HE (LHE). Each of these HE extensions have their own pros and cons and thus, by considering them we have considered BBHE, CLAHE, BPDHE, BPDFHE, and DSIHE enhancement algorithms, which are based on Mean Brightness Preserving HE and Local HE, for this study. The performance is evaluated with non-reference performance measures like Entropy, UCIQE, UICM, and UIQM. In this study, we apply the enhancement algorithms on 300 images from the UIEB benchmark dataset and then apply the techniques of cascading fusion on the best-performing algorithms.

Key words:
Cascading Fusion; Local HE; Mean Brightness Preserving HE; Underwater Image Enhancement; UIEB

1. Introduction

In correspondence to the applications of marine engineering, oceanographic engineering, oceanic engineering, or nautical engineering, there is a need for high-quality images. The purpose of these applications is the exploration of life under the water. However, images obtained from underwater tend to be of impaired quality, which has expressed the requirement of underwater image enhancement. Hence, we focus on enhancing three hundred underwater images taken from the UIEB benchmark dataset.

For this study, we have considered histogram equalization-based image enhancement algorithms. To classify them in a broader way, the annexes of HE methods are Global Histogram Equalization (GHE), Bin Modified HE (BMHE), Mean Brightness Preserving HE (MBPHE), and Local HE (LHE) [1][2]. As the name suggests, GHE performs global enhancement, regardless of the image's local contents. In MBPHE, mean brightness is preserved in order to maintain artistic significance. MBPHE is also able to avoid anomalous enhancement and reduce the saturation effect [2]. In BMHE, the image's histogram shape is modified by increasing/decreasing histogram's bins' value based on a defined threshold limit before application of equalization, however, in LHE a local transform is defined for every pixel based on its adjacent neighboring pixels. MBPHE, BMHE, and LHE are variations of GHE that were proposed to overcome certain drawbacks observed in GHE [2].

In this study, we have considered a few Mean Brightness Preserving HE and Local HE-based algorithms, such as BBHE [15], CLAHE [16], BPDHE [17], BPDFHE [18], and DSIHE [19]. We have also experimented with cascading fusion on the best two algorithms obtained, based on various performance measures like Entropy, UCIQE, UICM, and UIQM.

The paper is further divided into various sections. In section 2, the prior research is described in section 2. Section 3 illustrates the methodology and results, while Section 4 concludes the study.

2. Related Work

A lot of research is carried out on enhancing underwater images. This section summarizes a few of the approaches.

Chongyi Li et al. [3] introduced an Underwater Image Benchmark Dataset (UIEB), which includes 950 real-world underwater images. Out of total, 890 reference images, and the rest 60 are challenging images. They have also proposed a CNN model, trained on the same benchmark dataset, Water-Net, as a baseline. They aim to extend the benchmark dataset with more challenging underwater images/videos to improve the performance of the Water-Net network. The limitation mentioned is the effect of backscatter, which is difficult to remove.

Sangeetha Mohan et al. [4] discussed fusion-based approach using methods like CLAHE, Gray World Algorithm, Gamma correction, and Multiscale fusion (Pyramidal fusion) on the FB dataset. This approach improves visual peculiarities of the images taken underwater furthermore aids in recovering the features and edges that faded in the underwater images. The images captured from a greater distance under the water still have limitations for color restoration in this approach.

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Yue Zhang et al. [5] have proposed a color correction and de-hazing approach for enhancing underwater images. They utilized a multiscale fusion approach that enhances the images using weighted maps. This method eliminates the local reddish effect, removes haze of the underwater image, reduces image noise, and corrects color cast.

C. Cai et al. [6] proposed a multi-step approach, to remove dynamic interference and reconstruct the image, thus improving image quality. The color and contour seem more natural, but an image with complex textures and low resolution has fewer details.

Xuelei Chen et al. [7] adapted a deep learning approach to eliminate the influence of environmental circumstances under the water and obtain visually appealing images by achieving higher scores in PSNR and SSIM metrics. Amazingly, this approach provides faster computation speed. The future scope is to integrate the spatial perception information of sensors for more accurate images.

D. Abin et al. [8] have proposed a fusion algorithm, which includes the use of 'Multi-Scale Retinex with Color Restoration (MSRCR)' and 'Dark Channel Prior (DCP)', that can enhance underwater images. Their results show that this method gives a 10% better Structural Similarity Index (SSIM).

3. Methodology

This work aims to enhance the image quality of underwater images using various histogram equalization-based image enhancement algorithms like BBHE, CLAHE, BPDHE, BPDFHE, and DSIHE. The performance of these algorithms has been compared using different performance measures and cascading fusion-based approach is adapted to check for improvements in image quality.

3.1 Dataset

The authors of [3] have scrutinized numerous real-world underwater image datasets like the SUN dataset, Fish4Knowlege dataset, MARIS dataset, Sea-thru dataset, and Haze-line dataset. These datasets were proposed to cover various aspects of image processing such as target detection and recognition, scene recognition and object detection, marine autonomous robotics, and many more.

The objective of the UIEB dataset contributed by [3] was to collect underwater images from various sources and get a diversity of underwater scenes in a larger quantity. The underwater images in this dataset are collected from various sources on Google and YouTube, and other related papers [10] - [14].

3.2 Methods

BBHE: It is a technique used to brighten the image. This algorithm increases the brightness level and detects the edges present in the image accurately. Such an enhancement improves the information provided in the image and supplies more beneficial information to carry forward to the other image processing techniques. It also aids in enhancing the picture contrast.

BPDHE: 'Brightness preserving dynamic histogram equalization (BPDHE)' is another histogram equalization-based image enhancement algorithm. This algorithm generates the output image, aiming to maintain the average intensity nearly equal to that of the input image.

CLAHE: 'Adaptive histogram equalization (AHE)' is another histogram equalization-based image enhancement method. But in the relatively homogeneous images, AHE tends to over-amplify the noise. However, 'Contrast Limited Adaptive Histogram Equalization (CLAHE)', a modified version of AHE, makes sure to reduce the over-amplification problem. CLAHE improves the visibility level of foggy/blurry images or videos.

BPDFHE: 'Brightness Preserving Dynamic Fuzzy Histogram Equalization (BPDFHE)' is similar to BPDHE, with the difference that it uses fuzzy statistics of digital images. The fuzzy-based image representation and image processing in this technique, manages the inexactness of gray level values, which results in enhanced performance. The execution time is reliant on image size and the histogram's nature.

DSIHE: 'Dualistic Sub-Image Histogram Equalization (DSIHE)', is analogous to BBHE. Rather than dividing based on the mean as in BBHE, the DSIHE method divides the image on the basis of gray level values, with 0.5 as the cumulative distribution value. HE is applied to the decomposed sub-images. These sub-images are merged to produce the DSIHE output image.

3.3 Comparative Analysis for Image Enhancement Algorithms

Experimentation with BBHE, CLAHE, BPDHE, BPDFHE, and DSIHE is evaluated and compared based on the performance measures such as Entropy, UCIQE, UICM, and UIQM as illustrated in Fig.1. The experimental results in Table 1. exhibit that amongst the individual performances of these image enhancement algorithms, CLAHE followed by BPDFHE have performed better concerning Entropy and UIQM. However, BBHE and DSIHE show high values for UCIQE and UICM. Hence, cascading fusion is applied to the images obtained as an output from CLAHE and BPDFHE algorithms. A similar fusion is applied to the resultant images from BBHE and DSIHE algorithms as illustrated in Fig.2.

After comparing the fusion results with the individual performances of the image enhancement algorithms, shown in Table 2, it is observed that the performance of the cascading fusion between CLAHE and BPDFHE is better considering the Entropy, UCIQE, and UIQM, while the fusion between BBHE and DSIHE shows better results just with respect to the UICM evaluation measure. The values in Table 1 and Table 2 are the average values of the evaluation measures applied on the considered 300 images from UIEB dataset. Fig. 3. graphically illustrates the results in Table 2.

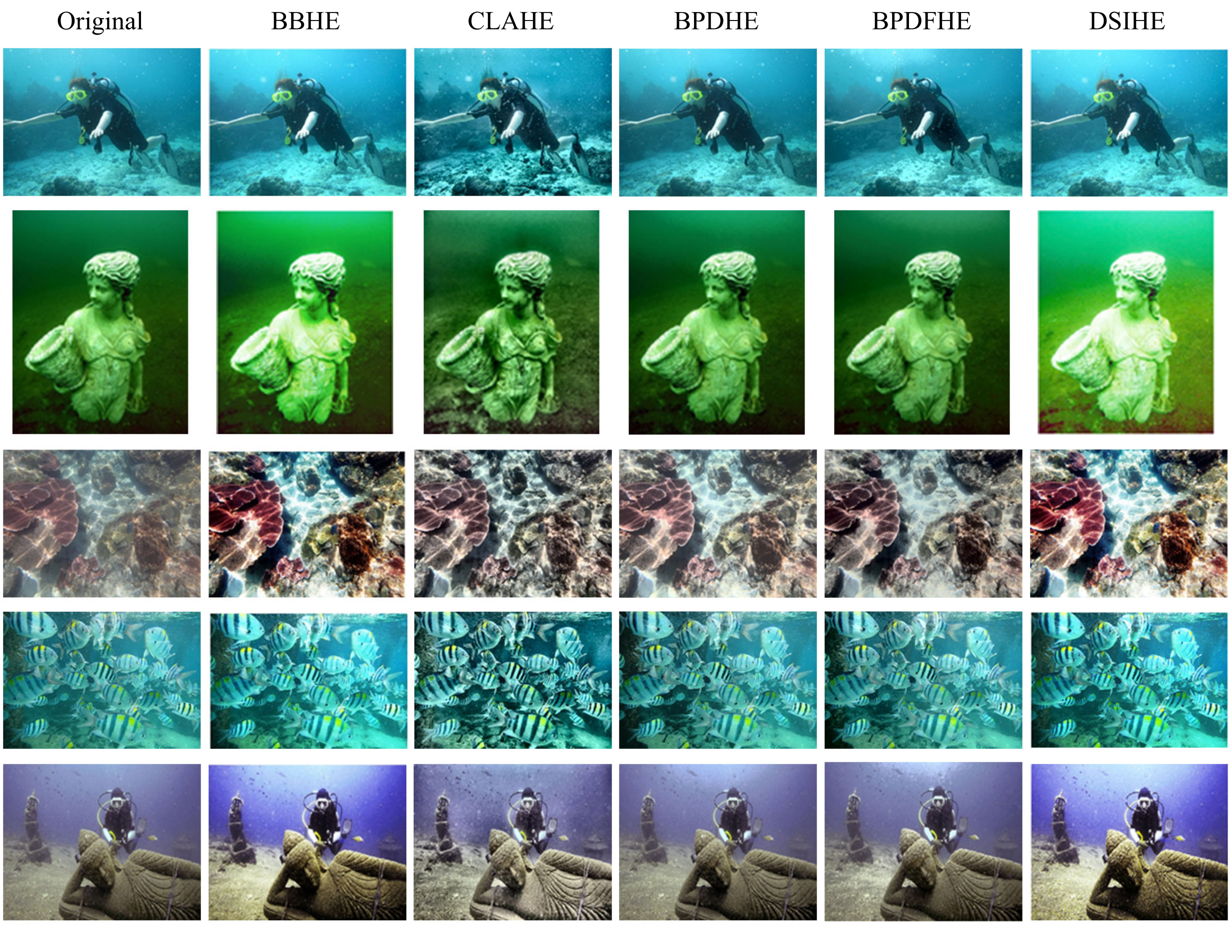

Fig. 1. Comparison of Images for outputs of BBHE, CLAHE, BPDHE, BPDFHE, and DSIHE algorithm

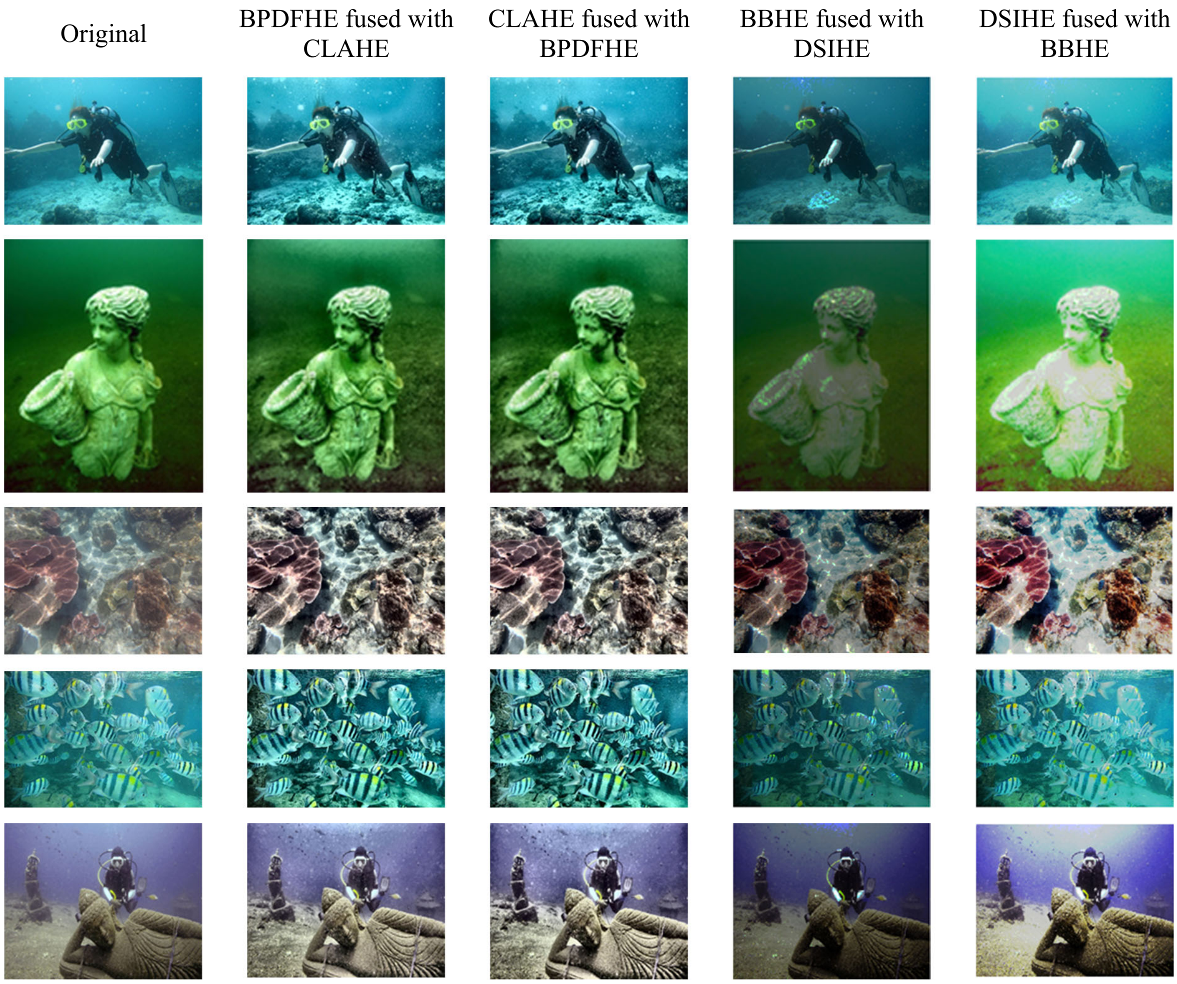

Fig. 2. Comparison of Images for outputs after cascading fusion applied on CLAHE and BPDFHE, and BBHE and DSIHE algorithms

Table 1: Comparative Analysis for Image Enhancement Algorithms

METRICS/ METHODS	**ENTROPY**	**UCIQE**	**UICM**	**UIQM**
BBHE [15]	1.4727	0.5907	-27.9124	1.8362
CLAHE [16]	6.9503	0.5713	-45.7386	3.3532
BPDHE [17]	6.5648	0.5505	-49.2404	2.6415
BPDFHE [18]	6.6216	0.5736	-47.9708	3.1136
DSIHE [19]	1.4884	0.5896	-30.3487	1.9873

Table 2: Cumulative Comparative Analysis of Histogram Equalization Algorithms and their Fusions

Metrics/ Methods	Entropy	UCIQE	UICM	UIQM
BBHE [15]	1.4727	0.5907	-27.9124	1.8362
CLAHE [16]	6.9503	0.5713	-45.7386	3.3532
BPDHE [17]	6.5648	0.5505	-49.2404	2.6415
BPDFHE [18]	6.6216	0.5736	-47.9708	3.1136
DSIHE [19]	1.4884	0.5896	-30.3487	1.9873
CLAHE + BPDFHE (Ours)	7.0315	0.5935	-44.6932	3.5526
BPDFHE + CLAHE (Ours)	7.0773	0.5866	-44.5995	3.4533
BBHE + DSIHE (Ours)	0.9599	0.5500	-7.3934	1.4973
DSIHE + BBHE (Ours)	0.9797	0.5423	-11.9915	1.6299

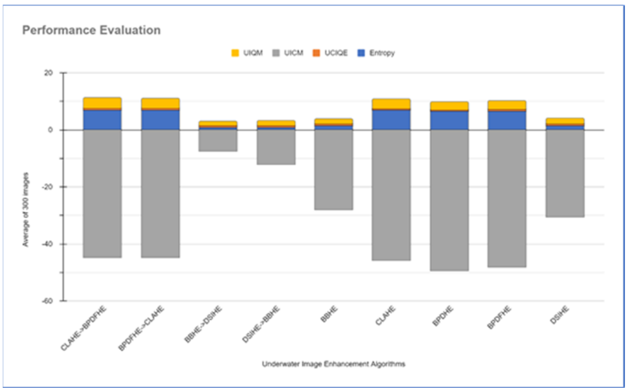

Fig. 3. Graphical Visualization of Comparative Analysis of Methods

4. Conclusion

The performance of these algorithms is evaluated and compared based on the performance measures such as Entropy, UCIQE, UICM, and UIQM. The experimental results reveal that CLAHE, followed by BPDFH, individually performed better than the other considered algorithms. Cascading fusion is also employed on the output images of CLAHE and BPDFHE algorithms. The fusion of BBHE and DSIHE gives better results just with regards to UICM, which indicates that the overall enhancement of the underwater images has not been taken care of. The observation of cascading fusion is that the fusion of CLAHE and BPDFHE histogram equalization algorithms give slightly better results than the individual performance of these two algorithms and other considered algorithms. As part of future research, various histogram equalization algorithms can apply different fusion techniques. The use of neural network-based models or bio-inspired models for image enhancements on underwater images with evaluation based on several performance evaluation measures could assist in obtaining significantly enhanced underwater images.

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References

[1] R. C. Gonzalez and R. E. Woods, Digital image processing, 2nd ed. Boston, MA, USA: Prentice-Hall of India, 2002.

[2] Nicholas Sia Pik Kong, Haidi Ibrahim, and Seng Chun Hoo, " A Literature Review on Histogram Equalization and Its Variations for Digital Image Enhancement," *International Journal of Innovation, Management and Technology* vol. 4, no. 4, pp. 386-389, 2013.

[3] C. Li, C. Guo, W. Ren, R. Cong, J. Hou, S. Kwong, D. Tao, “An Underwater Image Enhancement Benchmark Dataset and Beyond,” IEEE Trans. Image Process., vol. 29, pp.4376-4389, 2019.

[4] Mohan, Sangeetha, and Philomina Simon. “Underwater Image Enhancement Based on HISTOGRAM Manipulation AND Multiscale Fusion.” *Procedia Computer Science*, vol. 171, 2020, pp. 941–950., doi: 10.1016/j.procs.2020.04.102.

[5] Zhang, Yue, et al. “An Approach for Underwater Image Enhancement Based on Color Correction and Dehazing.” International Journal of Advanced Robotic Systems, vol. 17, no. 5, Sept. 2020, p. 1729881420961643. SAGE Journals, doi:10.1177/1729881420961643.

[6] C. Cai, Y. Zhang, and T. Liu, "Underwater Image Processing System for Image Enhancement and Restoration," 2019 IEEE 11th International Conference on Communication Software and Networks (ICCSN), 2019, pp. 381-387, doi: 10.1109/ICCSN.2019.8905310.

[7] Chen, Xuelei, et al. “Underwater Image Enhancement Based on Deep Learning and Image Formation Model.” ArXiv:2101.00991 [Eess], Jan. 2021. arXiv.org, http://arxiv.org/abs/2101.00991.

[8] D. Abin, B. Gulabani, C. Joshi, S. Damle and S. Gengaje, "Fusion based approach for Underwater Image Enhancement," 2021 International Conference on Communication information and Computing Technology (ICCICT), 2021, pp. 1-5, doi: 10.1109/ICCICT50803.2021.9510127.
[9] Abin, Deepa and Thepade, Sudeep D. and Gadde, Varun and Upganlawar, Vedant and Karpe, Sanskruti and Jadon, Vaishali Singh, Weighted Blending Fusion for Low Illumination Imagery Enhancement (July 9, 2021). Proceedings of the International Conference on IoT Based Control Networks & Intelligent Systems - ICICNIS 2021, Available at SSRN: https://ssrn.com/abstract=3883452 or http://dx.doi.org/10.2139/ssrn.3883452
[10] T. Treibitz and Y. Schechner, "Active polarization descattering," IEEE Trans. Pattern Anal. Mach. Intell., vol. 31, no. 3, pp. 385-399, 2009.
[11] C. Ancuti, C. O. Ancuti, and P. Bekaert, "Enhancing underwater images and videos by fusion," in Proc. of IEEE Int. Conf. Comput. Vis. Pattern Rec. (CVPR), 2012, pp. 81-88.
[12] X. Fu, Z. Fan, and M. Ling, "Two-step approach for single underwater image enhancement," in Symposium. of IEEE Intell. Signal Process. Commun. Syst., 2017, pp. 789-794.
[13] X. Fu, P. Zhang, Y. Huang, et al., "A retinex-based enhancing approach for single underwater image," in Proc. of IEEE Int. Conf. Image Process. (ICIP), 2014, pp. 4572-4576.
[14] A. Galdran, D. Pardo, and A. Picn, "Automatic Red-Channel underwater image restoration," J. Vis. Commu. and Image Repre., vol. 26, pp. 132- 145, 2015.
[15] Yeong-Taeg Kim, "Contrast enhancement using brightness preserving bi-histogram equalization," in IEEE Transactions on Consumer Electronics, vol. 43, no. 1, pp. 1-8, Feb. 1997, doi: 10.1109/30.580378.
[16] Zuiderveld, Karel. "Contrast Limited Adaptive Histograph Equalization." *Graphic Gems IV*. San Diego: Academic Press Professional, 1994. 474–485.
[17] H. Ibrahim and N. S. Pik Kong, "Brightness Preserving Dynamic Histogram Equalization for Image Contrast Enhancement," in IEEE Transactions on Consumer Electronics, vol. 53, no. 4, pp. 1752-1758, Nov. 2007, doi: 10.1109/TCE.2007.4429280.
[18] D. Sheet, H. Garud, A. Suveer, M. Mahadevappa and J. Chatterjee, "Brightness preserving dynamic fuzzy histogram equalization," in IEEE Transactions on Consumer Electronics, vol. 56, no. 4, pp. 2475-2480, November 2010, doi: 10.1109/TCE.2010.5681130.
[19] Y. Wan, Q. Chen, B.M. Zhang, "Image enhancement based on equal area dualistic sub-image histogram equalization method," IEEE Trans. Consumer Electronics, Vol.45, pp.68-75, 1999.

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