

Underwater Image Restoration using Machine Learning Algorithm

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Abstract— This work presents a comprehensive underwater image processing system designed for deep- sea research with the goal of mitigating the negative impacts of dynamic interference and water conditions. The method reconstructs precise underwater maps and improves image quality through a multi-stage process. The dark channel prior and an upgraded grey world method are initially used to provide contrast enhancement and color correction while accounting for underwater distortion. In order to guarantee the accuracy of the reconstructed image, dynamic interference, such as moving objects or disturbances, is then located and eliminated. An improved total variation model is used to balance resolution preservation with completeness, ensuring no important information is lost, in order to address blank areas left behind after interference removal. Ultimately, super-resolution is achieved by using an enhanced back-propagation network, which improves image details.

Keywords— Color balance, Histogram stretching, Fusion algorithm, underwater images, and Contrast optimization.

I. INTRODUCTION

G. Ramkumar The efficient management of underwater images is one of the most significant challenges in underwater robotic activity estimation. Apart from the well-known challenges of automatically deciphering images to connect with the outside world, underwater robotics faces further challenges arising from image deterioration due to light waves traveling through water. The development of autonomous robots that can navigate and interact in the mysterious underwater environment requires a precise understanding. Water's special optical characteristics present a unique set of

problems that call for advanced solutions to deal with problems like decreased contrast, distorted imagery, and reduced visibility. These elements increase the difficulty of image analysis in submerged environments, requiring sophisticated algorithms and image equations, graphics, and tables are not prescribed, although the various table text styles are provided. The formatter will need to create these components, incorporating the applicable criteria that follow [1].



Fig. 1. Diverse Underwater Image [2]

The underwater industry faces risks like shipwrecks in submarine robotic activities, despite the fact that it offers a wide range of applications. Operations were previously carried out by pilots with specialized training using remote vehicles (RVs) with tethered cables. But in the last few decades, there has been a radical change toward more autonomous infrastructure. Modern advanced technologies are being incorporated into autonomous underwater vehicles (AUVs) and remotely operated vehicles (ROVs) to improve autonomy, navigation, and decision-making. This evolution facilitates quick emergency responses by increasing operational efficiency and safety in hazardous underwater environments. Even with these developments, continuous efforts center on upholding strict safety regulations and incorporating fail-safe components into autonomous systems. To process sequential underwater images into a static map, a novel multi-step system is proposed. The system consists of pre-processing for contrast enhancement and color correction using a modified gray world algorithm and dark channel prior. After enhancement, object removal, in painting with an improved TV model, and super-resolution using an upgraded BP network are used for image restoration [3].

II. RELATED WORKS

A. Related Works

C. Li, J. Guo et al proposed “Underwater conditions present challenges for underwater imaging”, despite its widespread use in scientific research and technology. The direct, forward, and back scattering components that make up an underwater image cause light absorption, contrast deterioration, and an unclear background for the image. With the help of this work, deteriorated underwater images will be restored for high-quality imaging. The color cast, green-blue hue, and poor visibility are the main issues with underwater images. A number of restoration techniques have been suggested, such as taking advantage of color channel disparities, fusing wavelength compensation and dehazing algorithms, applying the dark channel prior algorithm, improving visual quality using fusion principles, and utilizing specialized equipment [4]. Weilin Luo for underwater images, three solutions are suggested: red channel histogram stretching, optimal contrast algorithm, and color balance algorithm. Underwater light attenuation patterns make traditional dehazing methods like DCP useless. Underwater and hazy conditions show different patterns of light attenuation. While photographs taken underwater exhibit high color deviation and decreased contrast, images taken in fog have similar histograms across all channels. This calls for specially designed algorithms for underwater situations. The suggested techniques seek to overcome these obstacles and raise the standard of underwater photography. The Optimized Contrast Algorithm deviates from improving transmittance and is a continuation of the Dark Channel Prior Dehazing Approach. Rather, it presents a new technique for determining transmittance. The approach improves contrast in underwater photos by expanding on the ideas of the dark channel prior without changing transmittance values directly.

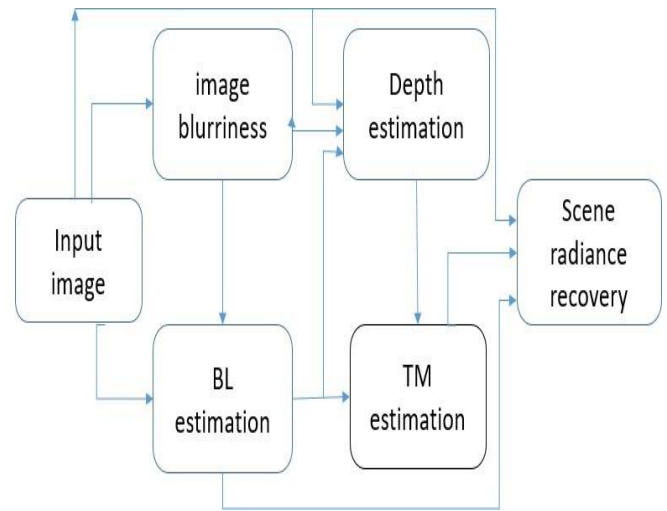


Fig. 2. Diverse Underwater Image [2]

Conventional methods might provide more effective contrast enhancement in difficult-to-access underwater. A histogram stretching algorithm is used to improve the brightness and contrast of underwater photos, with particular attention to the red channel. Red light is significantly attenuated in water due to the selective absorption of different hues by water, especially in deep water. Red channel problems result from many picture enhancing algorithms' tendency to overcompensate for this attenuation. The suggested approach uses histogram stretching depending on red light intensity to address this. The algorithm's goal is to reduce overcompensation and improve underwater image quality by adjusting the stretching operation to the properties of red light [5]. G. Sequeira uses two methods of sections for underwater image restoration. Image enhancement and restoration were created to address issues that are common in underwater environments. Because the blue channel is more susceptible to attenuation in underwater settings, they use the dark channel method, which is generally applied to terrestrial pictures. In order to restore visual clarity and contrast, this adaptation makes it possible to precisely collect and adjust for light absorption and scattering. They compensate for the attenuation of blue light by focusing on the blue channel, which, in contrast to the more constant red channel, exhibits varying intensity under underwater settings. Using methods like contrast adjustment, color correction, and noise reduction that are specific to the subtleties of underwater cinematography, they further enhance the restored photos in the Image Enhancement step combining the steps of enhancement and restoration. This method provides a complete way to enhance the underwater photographs' visual quality and interpretability. This method has potential for a number of uses, such as undersea exploration, industrial inspection, and scientific study, where precise analysis and decision-making depend heavily on crisp, detailed imagery [6]. With applications ranging from environmental monitoring to marine biology, underwater imaging is essential to oceanic engineering research. Even with improvements in recording technologies, like waterproof cameras, visibility, contrast, and illumination issues frequently plague underwater photos. Water

containing organic particles absorbs and scatters light, degrading its color and creating haziness. This paper uses a comprehensive approach that combines restoration and enhancement techniques to address the problems related to underwater image quality. Degradation of underwater image quality is caused by light absorption and scattering, which are impacted by turbidity and density of the water. The gradual loss of color with depth is caused by an increase in absorption rates in conjunction with turbidity [7].

III. PROPOSED WORK & IMPLEMENTATION

This work takes the reader on an intriguing underwater exploration by demonstrating how Convolutional Neural Networks (CNNs) can perform a mysterious metamorphosis, converting unprocessed underwater images into captivating, magnified versions. These improved photos make captivating starting points for further photo-editing explorations. In an intriguing detour, our expedition is led by clinical analysis, which establishes a sample size of 20 for Group 1 and another for Group 2, for a total of 40 samples between the two groups. The stage is set for discovery with the attraction of statistical intrigue, an alpha value of 0.05, a threshold set at 90%, and a pretest power of 80%. There's more to the story, though! The pictures that were used to train this neural magician have already been examined and examined.

A. DNN

The exciting idea of DNN-Histogram Equalization combines the concepts of standard image processing methods such as histogram equalization with the principles of Deep Neural Networks (DNNs). This is an explanation of the idea. An artificial neural network class known as DNNs has more than one layer between the input and output layers. Through the processes of forward propagation and backpropagation, they can learn intricate patterns in data, which gives them the ability to carry out tasks like image processing, regression, and classification.

B. Histogram Equalization

In image processing, histogram equalization is a technique that increases contrast by redistributing pixel intensities, enhancing feature visibility, and improving overall image clarity. By redistributing the pixel intensity levels, histogram equalization is a time-tested image processing approach that enhances contrast. It operates by first calculating the image's pixel intensity histogram, which is then stretched or compressed to produce a more uniform image. It functions by altering a picture's intensity values to produce an output image with a roughly uniform histogram. It functions by altering a picture's intensity values to produce an output image with a roughly uniform histogram. Histogram equalization is a straightforward yet powerful method for improving picture contrast. Images with poor contrast or uneven lighting conditions can benefit most from it. It should be used with caution though, as it can also magnify noise in the image. Additional methods could be required to lessen this effect, particularly in noisy photographs.



Fig. 3. Images(Left) and their corresponding reference Images(Right)

C. DNN - Histogram Equalization Algorithm

Initialization .

Input : 2D Matrix from Dataset. **Output** : Restored 2D Matrix.

Step 1 : Input 2D Matrix.

Step 2 : Convert RGB image to gray scale.

Step 3 : Apply Histogram Equalization :

$$s_k = T(r_k) = (L-1) \sum_{j=0}^k p_r(r_j)$$

Where ; S_k = Processed Intensity.

k = the intensity range ($0 \dots L-1$)

r_k = input intensity.

Step 4 : Train model with DNN parameters.

Step 5 : Load model.

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Step 6 : Test model.

Step 7 : Pertain accuracy by Precision and Recall.

Step 8 : End

In the initialization step of the procedure, a 2D matrix is supplied from a dataset. The RGB image is transformed to grayscale in the next phase, making the analysis that follows easier. The image's contrast is then improved by applying histogram equalization. Using the input intensity (r_k) within the intensity range ($0 \dots L-1$), where L is the highest intensity level, processed intensity values (S_k) are assigned. Next, a model of a deep neural network (DNN) is trained using given parameters. The model is loaded for testing in the subsequent stage after training. To make sure the model is effective, its performance is assessed in terms of recall, accuracy, and precision. Precision quantifies the percentage of positively anticipated cases that are accurately predicted among all cases projected.

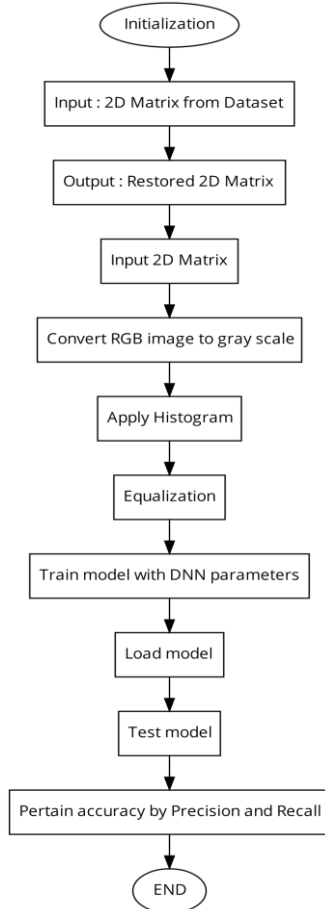


Fig. 4. Flow Chart

IV. RESULT OUTCOMES

Table No. I Comparison of PSNR for various underwater images

M Sudhakara (using L*A*B) [7]	Proposed Cluster 1	Proposed Cluster 2	Proposed Cluster 3
PSNR	PSNR	PSNR	PSNR
8.48	23.06	23.82	23.78
12.03	23.62	23.04	23.34
12.10	23.38	23.03	23.58
9.55	24.53	24.46	23.89

Table No. II Comparison of MSE for various underwater images

M Sudhakara (using L*B*A) [7]	Proposed Cluster 1	Proposed Cluster 2	Proposed Cluster 3
MSE	MSE	MSE	MSE
3971.15	255.38	269.57	272.82
2927.96	282.02	322.21	272.82
5780.31	298.34	161.92	301.16
4496.67	288.21	260.46	265.89

V. CONCLUSION & FUTURE SCOPE

This work explores new ground in the quest for visual perfection by utilizing a state-of-the-art Deep Learning technique: the deployment of a Convolutional Neural Network (CNN) for real-time image dehazing. In an exciting contest to prove its superiority in image enhancement, CNN takes on the traditional Support Vector Machine (SVM) algorithm. This effort is special because it uses selective reconstruction algorithms on purpose, which adds a level of complexity that goes beyond traditional interference. This purposeful intricacy guarantees that the neural framework is a sophisticated dehazing maestro, able to handle the most difficult scenarios, rather than just an approximation tool. Envision a world in which instantaneous visual clarity is the norm rather than merely a desired outcome. The developed neural structure reveals it.

REFERENCES

- [1] G. Ramkumar, A. G. S. K. M. M. Ayyadurai and S. C. "An Effectual Underwater Image Enhancement using Deep Learning Algorithm," 2021 5th International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India, 2021.
- [2] Underwater Image Restoration and Enhancement via Residual Two-Fold Attention Networks, Bo Fu and Liyan Wang and Ruizi Wang and Shilin Fu and Fangfei Liu and Xin Liu, 2020, International Journal of Computational Intelligence Systems, volume 14, issue 1.
- [3] 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), Chongqing, China, 2019.
- [4] C. Li, J. Guo, S. Chen, Y. Tang, Y. Pang and J. Wang, "Underwater image restoration based on minimum information loss principle and optical properties of underwater imaging," 2016 IEEE International Conference on Image Processing (ICIP), Phoenix, AZ, USA, 2016.
- [5] W. Luo, S. Duan and J. Zheng, "Underwater Image Restoration and Enhancement Based on a Fusion Algorithm With Color Balance,

- Contrast Optimization, and Histogram Stretching," in IEEE Access, vol. 9.
- [6] G. Sequeira, V. Mekkalki, J. Prabhu, S. Borkar and M. Desai, "Hybrid Approach for Underwater Image Restoration and Enhancement," 2021 International Conference on Emerging Smart Computing and Informatics (ESCI), Pune, India, 2021.
- [7] O. K. Athira and J. Babu, "Underwater Image Restoration using Scene Depth Estimation Technique," 2020 Third International Conference on Smart Systems and Inventive Technology (ICSSIT), Tirunelveli, India, 2020.