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Enhancement of Underwater Images using Texture Distribution Mapping Method

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Abstract

In either situation, underwater vision is affected by low light, diffraction, and color aberrations that lead to image distortion. To prevent this, we implemented a Texture Distribution Mapping Approach for undersea image improvement using MATLAB. Under this framework, we will enhance texture distribution, contrast, and visibility in general by controlling the most relevant properties of texture in the underwater environment. The TDM process is incremental: it involves pre-processing to eliminate noise and color distortion, followed by enhancement using another method for texture improvement. By enhancing texture mapping onto the image, we achieve a balance of visibility in high-texture regions, resulting in low-texture regions and better clarity and coloring. The method was compared against real underwater image data sets and tested for performance using quality measures like UCIQE (Underwater Color Image Quality Evaluation) and UIQM (Underwater Image Quality Measure). Experimental results and MATLAB implementation of the proposed algorithm exhibited stunning improvements in image quality and luminosity enhancements in texture compared to baseline methods, especially in challenging water conditions.

Keywords: UCIQE, UIQM, TDM, MSE, PSNR.

1. Introduction

Explanation underwater, and setting objects in view well above water at the same time, is needed to record unusual and infrequent events underwater. The use of underwater vision

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should be applied to technology and scientific applications in the examination of structure, determination of objects, and research. The mechanism of water for the transmission of light is the cause of color leaching and distant objects appearing white and indistinct. Attenuation and scattering of light are prominent causes of image loss when images are subaqueous, rendering the clarification subaqueous, and making it impossible to view object movement completely above the water at once, which is unavoidable in capturing great and surrealistic phenomena subaqueous. Visualization underwater is also critical in the application of technology and science in structural inspection, object recognition, and exploration. Light underwater causes fading out of sight and whitening of color, turning distant objects white and fuzzy. Attenuation and light scattering are the most prevalent image degrading factors whenever images are underwater, making the application of standard means of enhancement ineffective. Attenuation and air light haze decrease the visibility and contrast of images. Understanding the value and definition of water attributes is the elimination of fog as the starting point in designing efficient underwater image enhancement. Despite the presence of some improvement methods, they are limited by certain natural factors. Marine science is extremely popular on a yearly basis, and scientists have accordingly started to explore the underwater world for different purposes. Techniques like laser line scanning and optical polarization imaging provide good-quality images, but nothing underwater can be sensed by optical cameras. Waterproof cameras are frequently used in underwater photography, but recovery might not always be possible due to the influence of scattering and absorption. Image processing is applied to sense and analyze image data, such as visualization of processed output, image enhancement, and pre-processing. Partial brightness defects, water effects, and turbidity in underwater environments are addressed through local contrast equalization and generalization methods. Control parameters should be utilized while performing operations such as scattering of light, color conversion, and artificial illumination during underwater robotics and oceanographic exploration. Underwater image aberration is mostly induced by color variation and light scattering.

Water light is of different wavelengths, and thus underwater vision becomes blue. Light gets scattered whenever the direction of motion of light is towards objects and upon reflection or deflection through water particles, making the photos blurry. The deflection of light rays by suspended particles creates blurry photos. Fig 1 illustrates how each of the various colors of light is absorbed at deeper or shallower depths, with the deepest one absorbed first. Red is lost first at around 3 meters, orange at 10 meters, yellow at 20 meters, green at 60 meters, and blue and purple much later at much greater depths. Observe from the diagram that blue light has the shortest wavelength and hence travels farthest in water, causing underwater worlds to turn blue. Red, having the longest wavelength, is absorbed very quickly and is the first to be lost. The prevalence of blue in underwater photography, along with muddy lightness and contrast, contributes to the pictures appearing colorless and dark.

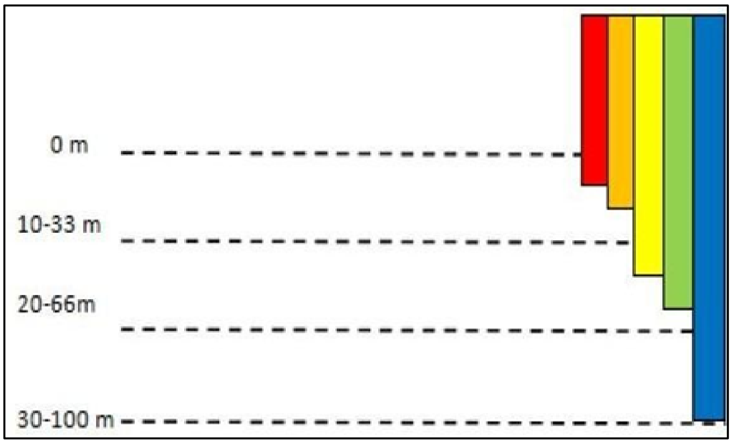


Figure 1. Variation of Color in Underwater Environment

Therefore, there should be improvement since scattering has an effect. Section 2 of this paper provides detailed background work on underwater image processing. Section 3 comprises the proposed methodology. The proposed research enhances underwater images based on a method known as texture distribution mapping. Texture recognition is of paramount significance in image research across the majority of fields. Section 4 comprises the results and interpretation. Section 5 elaborates on the conclusion and the way forward in the future.

2. Related Works

Underwater image restoration has advanced significantly, transcending the limitations imposed due to color aberration, low contrast, and blurring due to underwater conditions. Li et al. [1] proposed an overall approach towards restoring underwater images as well as videos using mapping techniques, enhancing visual quality and structure preservation. Further, Zhou et al. [2] also introduced a deep-learning-based unsupervised method for underwater turbid environments with less dependence on labeled data and more flexibility. More generally, Raveendran et al. [3] gave a wide-ranging review of existing improvement techniques, including the main challenges such as light variations, scattering, and field deployment. Recent advances have addressed some specifics of the image degradations. Lin et al. [4] focused on the recovery of texture and the reconstruction of structural detail, proposing an underwater image sharpening technique that recovers high-frequency details while preserving global image consistency. Zhou et al. [5] introduced a pixel distribution remapping and multi-prior Retinex approach to enhance global and local features of underwater scenes.

Zhang et al. [6] filled in the gap for diminished color channels using a method of correction that preserved detail and contrast while also restoring color balance: an essential application in deep-sea images. More recent techniques take advantage of more sophisticated learning methodologies. Hu et al. [7] proposed texture-aware, color-consistent enhancement algorithms, utilizing perceptual features to enhance visual realism. Wang et al. [8] employed deep statistical learning to train image degradations and obtained enhanced performance in different underwater scenarios. Liang et al. [9] combined color, detail, and contrast restoration techniques and obtained significantly improved image quality and fidelity. Tian et al. [10] proposed a feature fusion neural network model that integrates multiple enhancement cues into a single model with both synthetic and real-world underwater image effectiveness.

3. Methodology

The research involves improving underwater images using a technique of texture distribution mapping. Texture classification is applicable in image analysis in different fields. The system involves a multi-scale fusion algorithm in order to produce two images from a white-balanced image and combine them with a fusion algorithm. White balancing removes color casts that occur due to absorption at depth and gamma correction rescales contrast. The second input is an unsharp-masked image obtained through unsharp masking. The final dehazed output is a combination of the parts put together based on calculated weights. Max RGB and Gray World pre-processing techniques are also utilized. The method uses texture mapping, sharpening, and fusion stages, and is different from baseline techniques in that it does not use white balancing and gamma, correction; rather, it utilizes textured and sharpened images. Overall, the process aims to maximize underwater image quality and naturalness through a systematic process of improvement. Figure 2 provides an overview of the texture distribution mapping based proposed method.

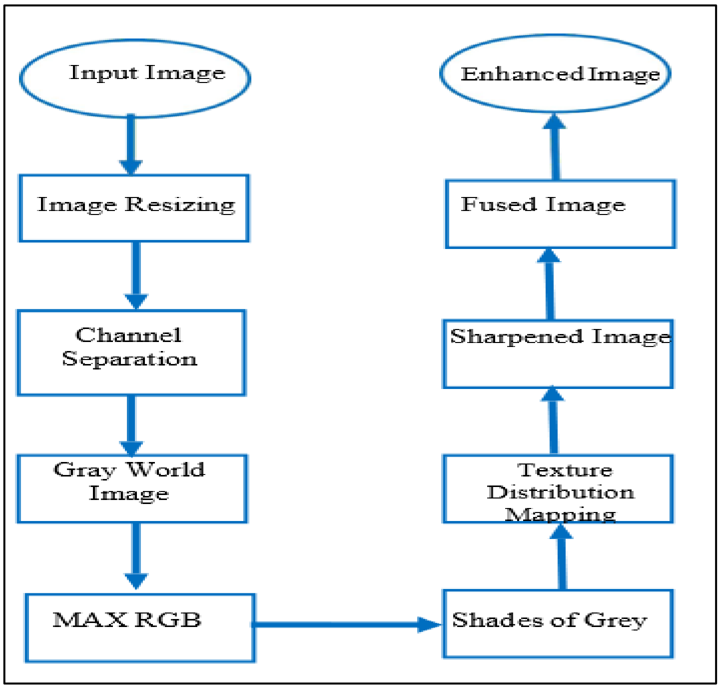


Figure 2. Overview of Texture Distribution Mapping Method

4. Implementation of Optimized Texture Distribution Mapping Method

The proposed algorithm is executed through the following steps:

Step 1: Input Image: The dataset of hazy underwater images serves as the input. These images are provided in either .jpg or .png format.

Step 2: Pre-processing: The collected images undergo a pre-processing phase. During this step, we apply the following techniques:

- **Gray World:** The Gray World algorithm operates on the premise that the average reflectance across a point is neutral in color. It enhances visual performance by estimating the color distribution through independent averaging of each color channel. By dividing each channel by its average value, the algorithm achieves color constancy.

- **Max RGB:** The Max RGB method operates on the premise that the maximum reflectance in a color channel originates from a white patch, which allows for the estimation of the light source's color by utilizing the highest response from various color channels. This technique is notably sensitive to the dynamic range of the human visual system.

- **Shades of Gray:** It has been noted that the Max RGB and Gray World techniques are specific instances of the Minkowski p-norm when executed on raw pixel data, particularly for $p = \infty$ and p

Step 3: Texture distribution mapping: The steps used in this method are as follows:

- First, patterns are extracted from each block of the image.
- Then, the pixel variation is estimated based on the center pixel and the binary pattern for the threshold limitations are obtained.
- The texture pattern for the obtained binary pattern is also estimated.
- The minimum and maximum values of the detected texture patterns are calculated.
- Then the slope and intercept of the straight lines are found.
- Finally, transformation of the image according to the formed new slope is performed and a stretched image without haze coefficients are obtained.

Step 4: Sharpening: To address the loss of detail during the enhancement process, the next phase involves generating a sharpened version of the image. In this step, image sharpening is done to magnify the edge regions of the image.

Step 5: Multiscale Fusion: In this step, the texture distribution mapped image and the sharpened image are fused together to finally attain the enhanced image. We have applied multi-scale fusion techniques to develop an effective method for enhancing underwater images. Image fusion involves merging valuable information from multiple images into a single composite image.

Step 6: Performance Measures: The performance like PSNR, MSE, UIQM, UCIQE and TIME.

5. Results and Discussion

This section illustrates the experimental comparison between baseline and proposed methods. Experimentation was conducted on a database of three sets of sample images. Implementation was done using MATLAB R2015a, and the JPEG format images were retrieved from www.bubblevision.com. The accuracy comparison of the methods relied on two approaches, namely subjective and objective measurements.

Subjective evaluation in accordance with the visual perception of team members in our research group, has been conducted as part of the subjective approach for image quality. Fig.

3 indicates that images obtained through the proposed process are of better quality compared to those from the baseline process. Evaluation of performance quantities has also been conducted by considering PSNR, mean squared error (MSE), underwater color image quality assessment, and underwater image quality measure (UIQM). PSNR is considered to be a function of the ratio of the maximum power of the signal to the power of the noise signal affecting the signal. The better the image quality, the higher is the PSNR. PSNR is measured in decibels, dB. MAX is defined as the largest pixel value; hence, PSNR in decibels can be expressed as:

$$PSNR = 10_{\log_{10}}\left(\frac{MAX_i^2}{MSE}\right) \tag{1}$$

$$PSNR = 20_{No}\left(\frac{MAX_i}{\sqrt{MSE}}\right) \tag{2}$$

$$PSNR = 20_{\log_0}(MAX_i) - 10_{\log_{10}}(MSE) \tag{3}$$

Mean Squared Error (MSE) finds the average of the squares of the deviations between actual and predicted values. It serves as an important metric for assessing an estimator's accuracy. Lower values of MSE, which are always non-negative, indicate better estimation and performance when near zero. The formula for the calculation of MSE is given below.

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2 \tag{4}$$

where I(i,j) and K(i,j) refer to the original and processed image intensities, respectively. The UCIQE (Underwater Color Image Quality Evaluation) index is designed particularly to assess image quality because it takes into account the color distortion resulting from light attenuation. This index, for an image I, is defined as follows:

$$UCIQE = c_1 \times \sigma_c + c_2 \times \mathrm{con}_l + c_3 \times \mu_s \tag{5}$$

Upon inspection, σc refers to the chroma variance, con i refers to luminance contrast, and μs is the saturation mean. The c_1, c_2 and c_3 are scale factors used to weigh these factors. The variance of chroma has been discovered to correlate very closely with human vision, particularly in color images underwater. Contrast is a value for the degree to which a target stands out when observed against an even background. To compute con i, we calculated the bottom 1% and top 1% difference in pixel luminance channel values. Note that contrast, chroma, and saturation are computed separately so that they can be processed in parallel, thereby accelerating overall processing. Underwater image correction coefficients for blurring, color cast, and marine snow distortions were determined to be $c_1 = 0.4680$, $c_2 = 0.2745$ $c_3 = 0.2576$. The UIQM is based on the human eye and takes into account the degradation of contrast. An increased value of UIQM is generally indicative of improved image quality, and improvements in UIQM scores are likely to induce substantial improvements in visual acuteness. The UIQM metric combines parameters such as UICM for colorfulness, UISM for acuteness, and UIConM for contrast, in order to derive a final assessment of underwater image quality. For Figure 2, the Underwater Image Quality Measure (UIQM) is based on parameters c_1, c_2 and c_3.

$$UIQM = c_1 \times UICM + c_2 \times UISM + c_3 \times UIConM \quad (6)$$

For the parameter selection, it is application-based, with UICM being emphasized for color correction processes and UIConM and UISM for visibility enhancement. Two parameter choices set to zero allow UIQM to emphasize particular underwater image characteristics.

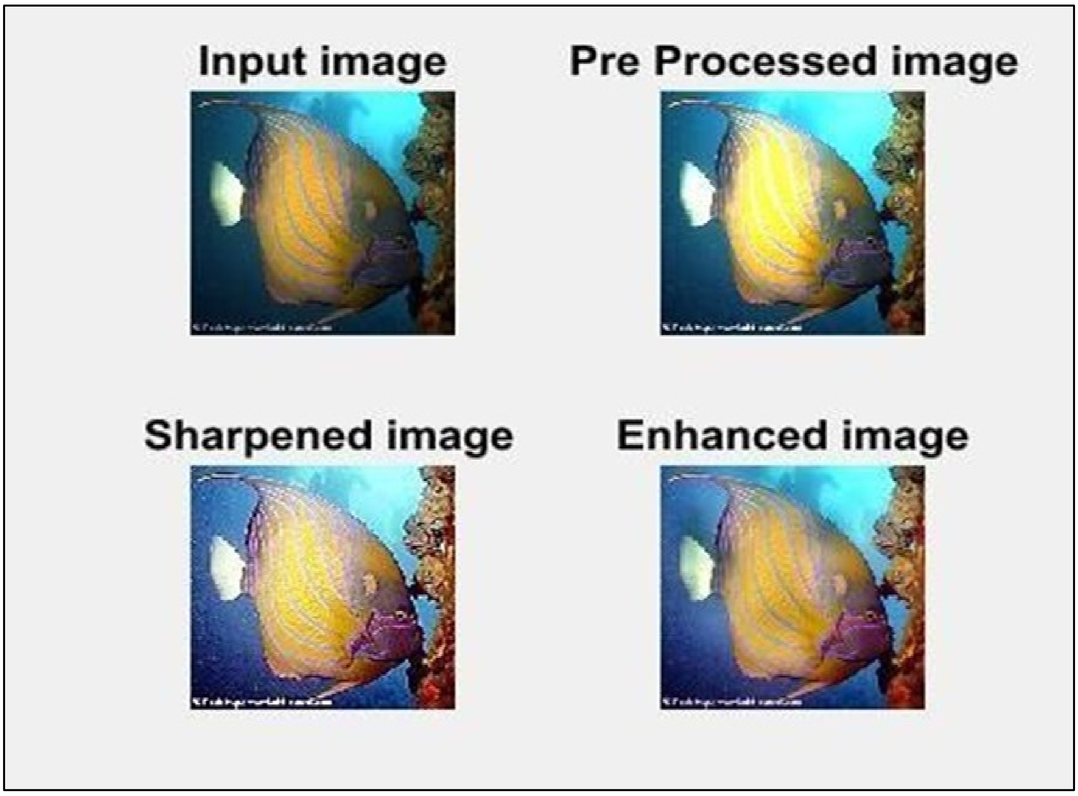


Figure 3. MATLAB Result Showing Input Image and Enhanced Image by Proposed Method

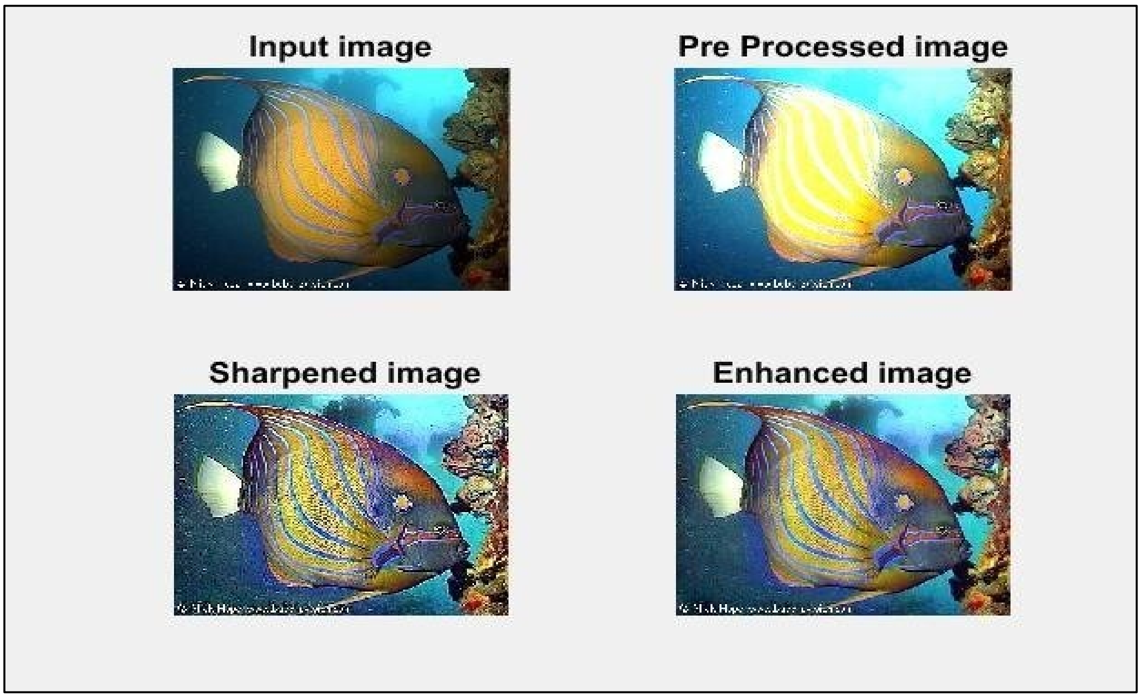


Figure 4. MATLAB Result Showing Input Image and Enhanced Image by Baseline Method

Table 1. Comparison Between Baseline Method and Proposed Method using PSNR and MSE

Input Image	**Enhanced Image**	**PSNR(dB)**		**MSE(db.)**	
		Baseline	**Proposed**	**Baseline**	**Proposed**
		43.72	73.57	2.76	0
		43.57	48.71	2.85	0.87
		44.03	49.46	2.56	0.73

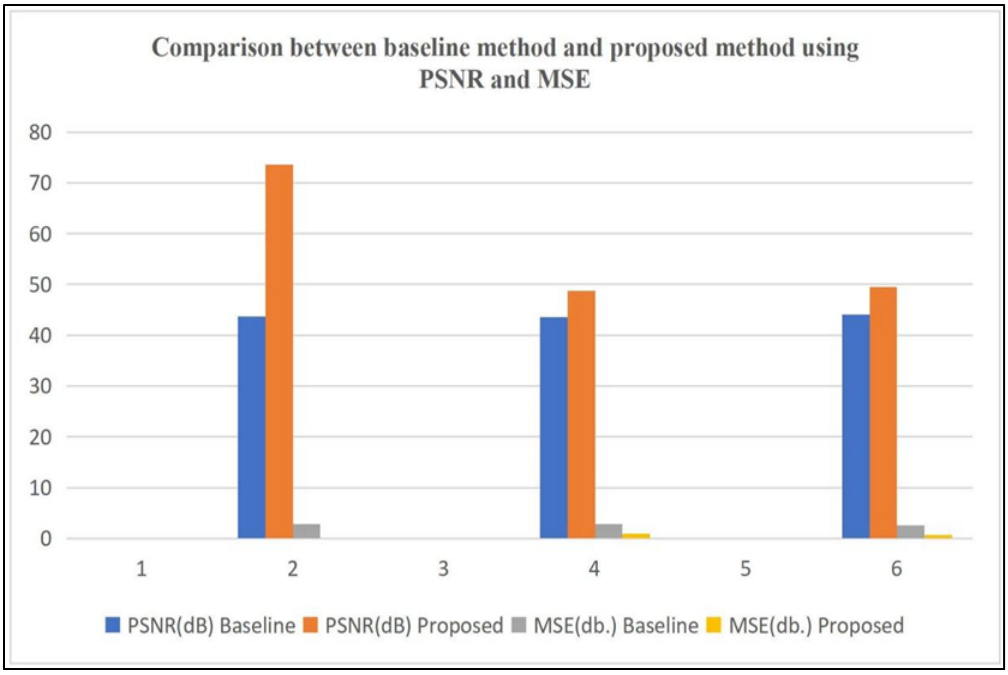


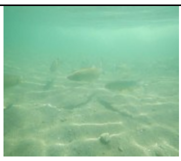
Figure 5. Comparison Between Baseline Method and Proposed Method using PSNR and MSE

In Table 1 Interpretation are,

- High PSNR implies superior signal quality since it reflects a more elevated signal-to-noise ratio. In your data, PSNR appears to be much higher for the Proposed method (73.57 dB) in one instance, implying superior performance relative to the Baseline. PSNR values (73.57, 48.71, and 49.46 dB) for the Proposed method imply various cases where a higher value indicates superior signal quality. Figure 5 demonstrates the comparison between the baseline approach and the proposed approach using PSNR and MSE.

- MSE measures the mean squared difference between the input and estimated signals. Lower MSE means greater accuracy. In the Proposed method, the MSE measures are 0 or extremely low (0.87 and 0.73), reflecting superb performance with very little error. Across all cases, the Proposed method has substantially lower MSE compared to the Baseline method. When the Proposed method has an MSE of 0, its PSNR also approaches a very high value (73.57 dB), indicating perfect performance under the said condition. The comparison indicates that, on average, the Proposed method performs better than the Baseline method according to PSNR and MSE measures.

Table 2. Comparative Analysis using UCIQE and UIQM

Input Image	Enhanced Image	UCIQE		UIQM	
		Baseline	**Proposed**	**Baseline**	**Proposed**
		0.45	0.13	1.89	1.89
		0.40	0.13	1.89	1.89
		0.35	0.15	1.89	1.89

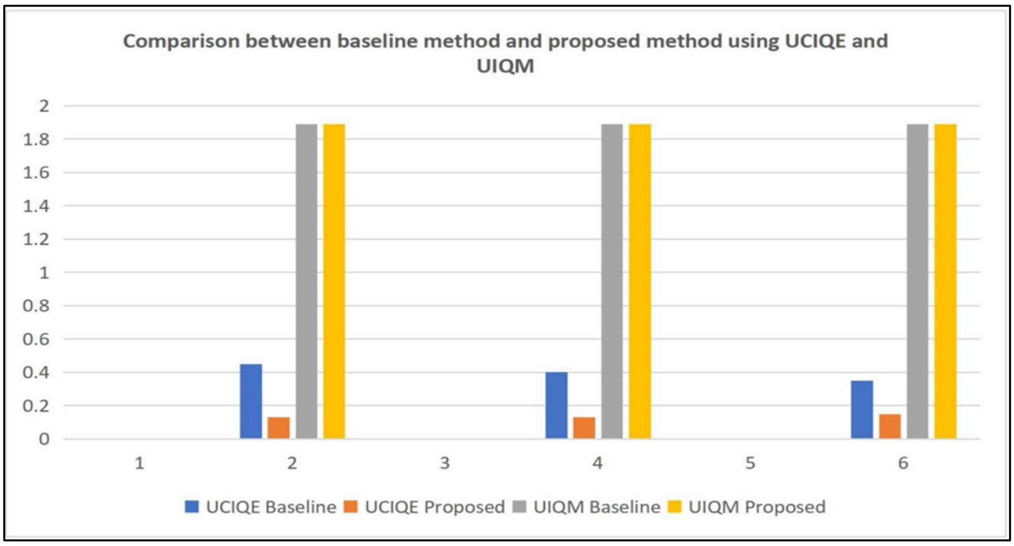


Figure 6. Comparison Between Baseline Method and Proposed Method using UCIQE and UIQM

In Table 2 Interpretation are,

- UCQIE measures the colorfulness, contrast, and sharpness of underwater images. According to these factors, the values in the Proposed method are 0.13 and 0.15, which are relatively low. From the above values, it can be inferred that the quality of the color images concerning the above variables is not excessively high.

- UIQM is a general quality measure of underwater image quality in terms of three factors: colorfulness (UICM), sharpness (UISM), and contrast (UIConM). The UIQM values of both the baseline and proposed methods for all scenarios are 1.89. This shows that the proposed method does not yield significant improvement in overall underwater image quality compared to the baseline.

Table 3. Comparison Between Baseline Method and Proposed Method using Computational Time

Input Image	Enhanced Image	TIME(Secs)	
		Baseline	Proposed
		10	8
		18	16
		16	8

6. Conclusion

We propose, in this paper, a way of improving underwater images using texture distribution mapping where the texture dimension is the image pattern's distribution. We have proven that it can be used to improve a wide class of underwater images either due to the unprecedented scene structure or due to scene orientation. Comparison with another class of images ensures that our proposed approach is better both quantitatively and qualitatively. Our algorithm is not perfect, though. On the one hand, with less noise and artifacts, at times it does not restore the color entirely. Furthermore, additional tuning must be done in order to be obtain more accurate numeric values of the Underwater Image Quality Measure than the baseline. Also, our method relies on some a priori knowledge, i.e., red light is absorbed by water more than any other lights. Where this is not the case-i.e., when illuminating over extensive black objects like a black wetsuited diver-our method can give false indications. But most underwater activity is highly illuminated and highly colored, so this never actually occurs. We will now outline these restrictions and then go on to outline the method. We will also allow for the process to be employed in further developing underwater-shot films.

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