An Improved Underwater Image Enhancement Approach for Border Security

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***Abstract*—Protecting maritime borders is crucial to ensuring overall border security. Law enforcement agencies make great use of analyzing images of underwater debris to gather intelligence and detect illicit materials. Underwater image improvement contributes to better data quality and analytical. Nevertheless, underwater image analysis poses greater challenges compared to analyzing images taken above the water, factors like refraction of light and darkness contribute to the degradation of underwater image quality. In this paper, a novel approach is proposed to enhance underwater images, the proposed approach involves splitting underwater colored image to its three basic components, Subsequently, a point spread function is created for each component to describes image blurring factor, The deblurring process is then applied by using wiener filter, the result sharped by sharping filter to clarify edges, contrast linear stretch is performed to improve contrast and visual details. and the resulting image is finally reassembled from the three basic components. The proposed method showed effective results in evaluating the main metrics and gave better results when compared to a number of different methods. These results prove the effectiveness of the proposed method and its ability to practical applications in improving image quality.**

***Keywords*—underwater images, image enhancement, deblurring, point spread function, wiener filter**

I. Introduction

Processing underwater images is one of the most important challenges in this field. In addition to the known difficulties in automatically interpreting the image for interaction with the environment, there are additional issues deriving from image quality degradation induced by light transmission in water [1].

Images captured underwater are frequently degraded due to scattering and absorption effects. These degraded underwater images show limitations when used for display and analysis. Low contrast and color cast are two prominent issues that impair the accuracy of underwater item detection and marine biology recognition [2].

Underwater image enhancement is crucial for clear, real-life underwater scenarios and marine life exploration research and border security. Degraded images tend to focus on green colors, resulting in less visual clarity. Enhanced images display more information and superior visual quality, as shown by the histogram distribution of red, blue, and green colors [2]. Therefore, enhancement methods are essential for obtaining high-quality underwater images for research and real-life applications. This underwater image enhancement approach aligns with countless Internet of Things (IoT) and 6G technologies [3], enhancing data quality and processing in underwater environments. It has applications in security, environmental monitoring, and advanced communications systems. Further research and development will likely lead to new underwater imaging and analysis applications [4].

Various image processing algorithms and methods have been proposed to enhance the visual quality of degraded underwater images by minimizing turbulence-related blur and distortion. Nutri *et al.* [5] proposed a fusion-based method for enhancing degraded images, incorporating weight maps to account for non-linear image corruption, and fused the improved images to generate an enhanced image, agnostic to image scene structure or underwater conditions.

Lyu *et al.* [6] present a Convolutional Neural Network (CNN)-based framework for enhancing underwater images. It consists of two stages: CNN-based enhancement and Luminance (Y), blue-luminance (U), and red-luminance (V) based post-processing. The CNN network extracts latent features, while the output is transformed to YUV color space for brightness improvement. Experimental results show superior performance. The proposed scheme conducted by Li *et al.* [7] uses an adaptive color and contrast enhancement and denoising framework, employing a Difference of Gaussian filter and bilateral filter to decompose high-frequency and low-frequency components. Soft-thresholding operation suppresses noise, while this strategy enhances low-frequency components.

In Ref. [8], a robust retinex model is presented for enhancing low light images that suffer from high levels of noise degradation. The optimization problem is addressed using an algorithm based on Alternating Direction Minimization (ADM). This approach proves to be

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effective not only for improving images in low light conditions but also for applications in remote sensing, as well as in environments affected by haze and dust. While Li *et al.* [9] introduces a two-stage dust removal approach. At the beginning, dust effect on the image must be eliminated. This is done by enhancing the red—green channels before scattering. then we remove the dust effect by using deep convolutional neural network.

In this paper proposes enhancing underwater images through applying the following steps. Firstly, the algorithm receives the underwater image as input with three channels, then the channels split to the original three channels Reg, Green, and Blue, which are the basic image components. Next, a Point Spread Function (PSF) is created which describes the blurring effect on the image. PSF helps in understand the type of noise the affect the image during image capturing. After that, Wiener filter applied to each channel. The image sharpened using a two-pixel radius filter and unsharp masking technique. This step is necessary to further enhance the image. After that, a contrast linear stretching is performed to each channel using lower and upper stretching limits obtained using MATLAB stretchlim method. These limits represent the lower limit that is determined through analyzing image histogram to select the appropriate percentile. This will help in exclude dim pixels and noise. Similarly, the upper limit is chosen to avoid overexposure by excluding bright pixels. The contrast stretching operation rescales the pixel intensities within these limits, expanding the dynamic range and improving contrast and visual details in the image.

The organization of the paper is as follows. Section II presents the optical turbulence of underwater and its effect on the images. Section III presents the methodology. Section IV evaluates and discusses the experimental results. Finally, in Section V, a conclusion is provided.

II. Optical Turbulence of Underwater

This phenomenon refers to the random fluctuations and variations in the properties of light propagating through water. This is caused by small fluctuations in temperature and salinity in the column's water, which lead to changes in the refractive the water index lengthways the path of light. These variations can have a significant impact on the propagation and quality of underwater optical signals, which can affect a range of applications such as underwater sensing, communications, and photography.

In optical systems operating underwater, turbulence-induced variations in the refractive index will cause light rays to bend and scatter, resulting in beam blurring and attenuation. As a result, visibility is decreased and image quality is compromised [1]. The many influences on underwater visual turbulence are depicted in Fig. 1.

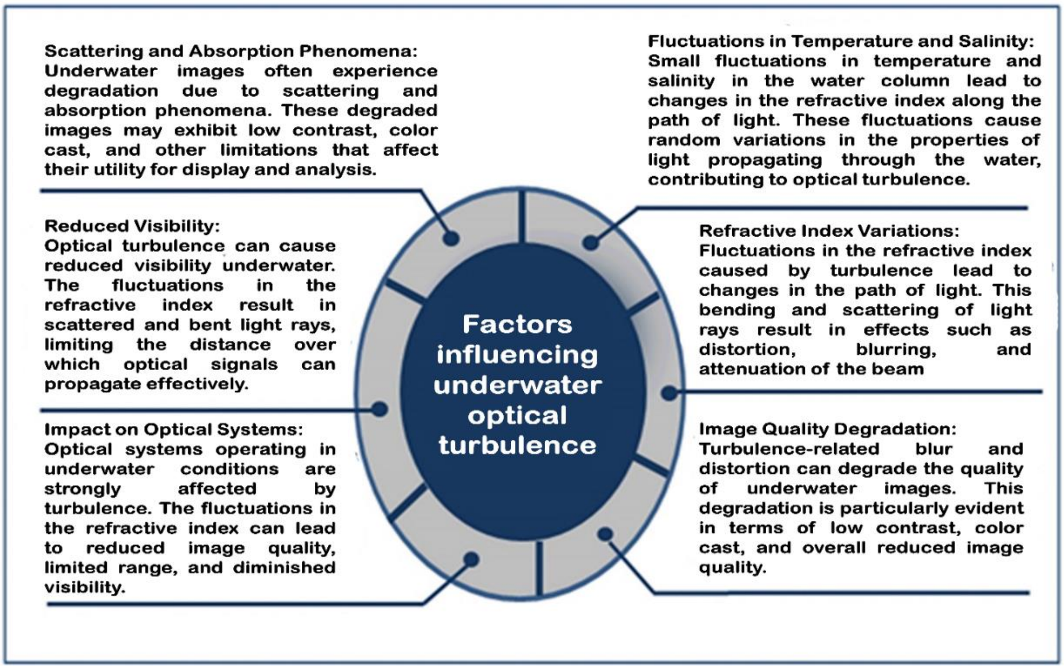

Fig. 1. The factors influencing underwater optical turbulence.

Other important factors that affect underwater turbulence are salinity and temperature. The fluctuations of these factors will greatly affect the refractive index of water and thus lead to changes in the optical properties of water resulting from turbulence. The latter results in multiple scattering because of variations in the refractive index. When the disturbance is weak, it has little effect; but, when the frequency and dispersion rise, the disturbance will get stronger and affect underwater photography, diver vision, and visual communications [2].

III. Methodology

The proposed approach includes several steps that are illustrated in Fig. 2, which are as follows.

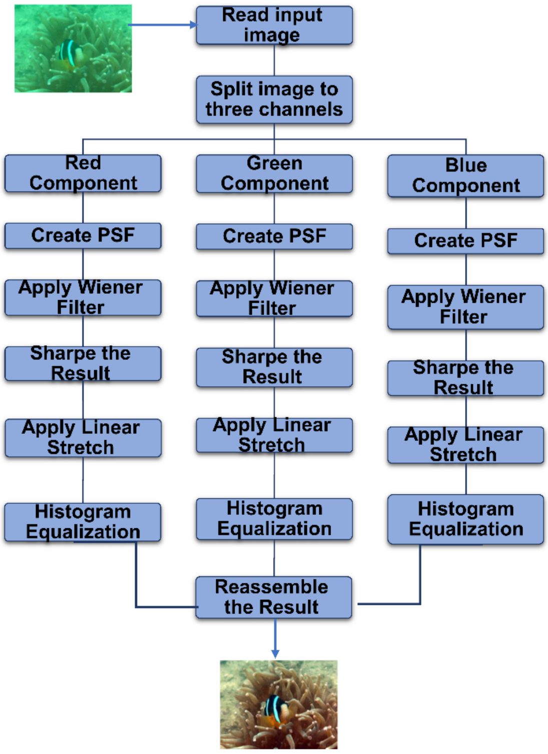

Fig. 2. The steps of proposed method.

A. Point Spread Function (PSF)

After reading the input image and splitting each channel of the Red, Green, Blue (RGB). This process result is three separate images: R image, G image, and B image. Each channel represents the intensity values of its corresponding color component.

Once the channels are separated, the next step is to create the PSF. The distortion or blurring applied to the image during the capture or imaging process is described by the PSF. It is a mathematical model of how light scatters or spreads through the image generation process.

The process of creating the PSF entails figuring out the blurring effect's properties, including its size, distribution, and shape. Depending on the obtainable imaging system information and exact blurring scenario, various techniques can be employed to estimate or simulate the PSF. Eq. (1) below displays the value of the PSF filter, which takes three arguments and return PSF as a result. the three arguments are the type of filter, which is motion in our case, the length which represents Linear motion of camera specified as a numeric scalar, measured in pixels, and the theta which represents Angle of camera motion in degrees, specified as a numeric scalar. Furthermore, two pixels with an angle of "theta" equal to 1 counterclockwise are explained below:

$$PSF = \begin{bmatrix} 0 & 0 & 0 \\ 0.2500 & 0.5001 & 0.2500 \\ 0 & 0 & 0 \end{bmatrix} \quad (1)$$

By separating the channels and establishing the PSF, we provide the groundwork for processing of images like deblurring, enhancing, or restoration.

B. Wiener Filter

To solve image blurriness problem, Wiener filter was applied to each channel of RGB image. PSF for each channel calculated individually and then applied to Red, Green, Blue channels respectively. PSF represent the factor that affect the image during image capture and procure the blurring effect. Image deblurring is the process of estimating the blurring factor then reversing the effects of blurring with the Wiener filter, this will make it feasible to estimate the original sharp image.

Applying Wiener filter performed via applying several steps on each channel of RGB image. At the beginning, PSF factor for every channel is calculated. Which is nothing but a mathematical representation of how blurring happens in that specific channel. After determining PSF, the Wiener filter computes a restoration filter using both the PSF and the power spectrum of the blurred image. After that, the restoration filter is applied to each channel of the RGB image separately. With the statistical characteristics of the blurring process taken into account, this filter reduces the mean square error between the current crisp image and the actual blurred image. A deblurred image is calculated through convolving each channel with the obtained restoration filter, which successfully reduces the blurriness brought on by the PSF.

In brief, the Wiener filter is used to deblur each channel of the RGB image through PSF estimating for each channel, restoration filter is calculated according to statistical estimation, then applied to each channel separately. This will cause to create a version of image as near as possible to the original image before the effect of deblurring factor**.**

C. Sharpening Process

After applying deblurring through Wiener filter, the image is further enhanced by sharpening its characteristics after being deblurred. This is done by using particular filter known as a 2-pixel radius filter. The sharping filter used to sharp the image, which mean it used to make the edges clearer, this filter transforms the final image in a way that draws attention to the edges and sharp the details. The 2-pixel radius filter applies the unsharp masking technique to improve the image's quality. Image sharping mask removes a blurring from the original image and highlight the high-frequency components that pertain to the edges and minor features. This step will result an image sharper than the original one.

The purpose of the sharpening process is to improve the image's edges, making it clearer and more defined. This procedure strengthens the image's internal edges and clarifies the details, which improves the image's overall visual impact. The final image is sharpened by combining the unsharp mask approach with the 2-pixel radius filter. Ultimately, the deblurred image has better features.

D. Contrast Linear Stretching

Contrast linear stretch is the process of re-distribute the intensity inside an image depending on its lowest and highest gray scale boundaries. The factor of contrast linear stretching is calculated and the applied to image to redistribute the intensity values inside it. In order to calculate these limitations, the image's pixel intensities must be examined, and suitable values must be chosen in order to accomplish the required contrast enhancement. In our proposed approach, we use contrast linear stretching on the image resulted in previous step. This will make image luminance more adequate to the viewer.

E. Histogram Equalization

Image histogram is the process of showing the frequency of appearing for each pixel inside the image. By taking the darkest fifth percentile and the highest fifth percentile of image intensity values, we can equalize the histogram of the image which excludes excessively dark pixels while also avoiding any noise or outliers in the image. Histogram equalization also enhances the brightest pixels and avoid overexposure. By setting the upper limit below the maximum intensity value, we ensure that the image's brightest portions are not overly stretched, maintaining features and avoiding clipping.

[low(Red),high (Red)]=Stretchlim(R)

[low(Green),high (Green)]=Stretchlim(G) (2)

[low(Blue),high (Blue)]=Stretchlim(B)

The contrast stretching is redistributing pixels intensity with particular range to encompass the complete grayscale spectrum after the lower and higher boundaries are defined. This process makes dark pixels closer to the dark gray values, and bright pixels closer to the bright values, which result to improved version of an image. This will be revealing fine details and enhancing visual quality.

IV. Results and Discussion

The primary goal in this part is to demonstrate the efficacy of our approach through experimental data, as shown in Fig. 3. Three widely used metrics were utilized to evaluate our method: MSE, PSNR, and SSIM. Fig. 4 shows these metrics.

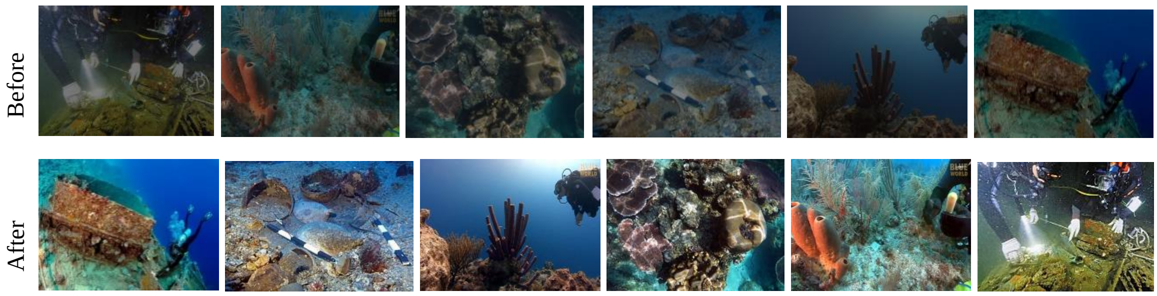

Fig. 3. Top row: degraded image and Bottom row: The result of proposed method.

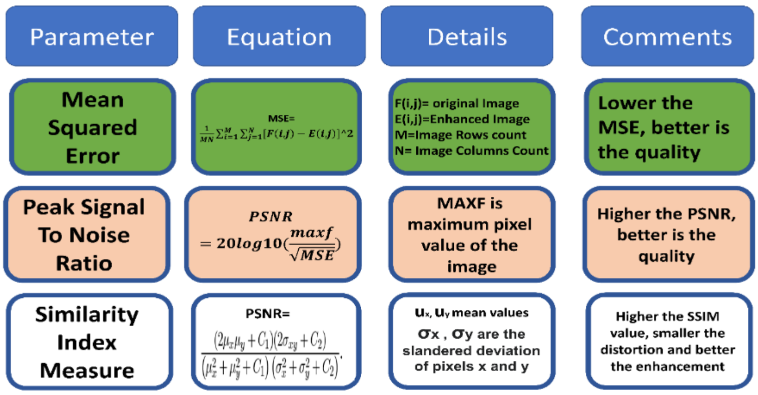

Fig. 4. The performance evaluation parameters of underwater image enhancement.

Table I shows the quantitative results of different techniques, with emphasis on Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR), and Structured Similarity Index Method (SSIM). These results are based on examination of the test group. We compared the results of our proposed method with these techniques. Notably, our method performed well in terms of quality assessment. The results obtained support the efficacy and superiority of our method to tackling the given problem.

MSE is an indicator that calculates the total squared error between an improved image and its original counterpart [10–15]. Improved image quality is measured using MSE, where a lower number means higher quality due to a lower error. As shown in Fig. 5, the suggested approach yields a reduced MSE value when compared to the values of methods Blurriness based [12], Histogram prior [13], GDCP [15], Water Cycle GAN [16], and the original image. While it gave larger values when compared to Water-Net [10], Dense GAN [11], Fusion based [14], and Retinex based [17].

PSNR is a common statistical indicator for evaluating enhanced image quality. It is an expression of the ratio of the maximum achievable signal strength to the strength of the corrupting noise present in the image. When the value of this indicator is high, this indicates improved image quality with low noise or distortion [18–19].

TABLE I. COMPARISON OF MSE, PSNR AND SSIM RESULTS OF PROPOSED METHOD WITH OTHER METHODS

Method	MSE	PSNR	SSIM
Water-Net [10]	0.7976	19.1130	0.7971
Dense GAN [11]	1.2152	17.2843	0.4426
Blurriness based [12]	1.9111	15.3180	0.6029
Histogram prior [13]	1.7019	15.8215	0.5396
Fusion based [14]	1.1280	17.6077	0.7721
GDCP [15]	4.0160	12.0929	0.5121
Water Cycle GAN [16]	1.7298	15.7508	0.5210
Retinex based [17]	1.2924	17.0168	0.6071
Original image	2.83171	17.3555	0.6168
Proposed method	1.60243	20.3610	0.7901

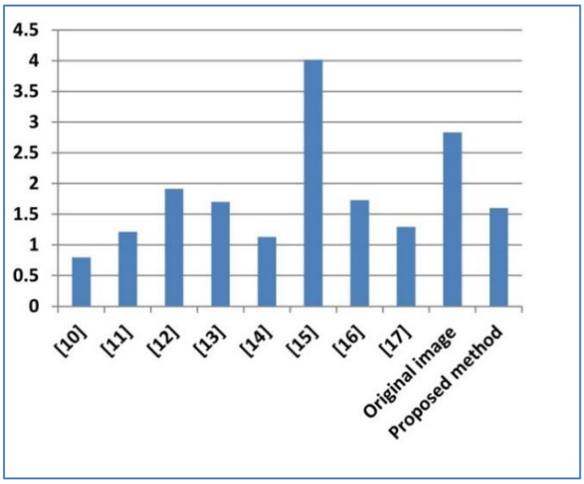

Fig. 5. Comparison of MSE result with other methods.

In the context of comparing the PSNR scale values of the proposed method with those of other methods, it becomes evident that the proposed method exhibits a higher PSNR value in comparison. Additionally, the proposed method's PSNR value surpasses even the PSNR value of the original image itself, as depicted in Fig. 6. The proposed method is effective in preserving image details and reducing noise, resulting in visually improved output.

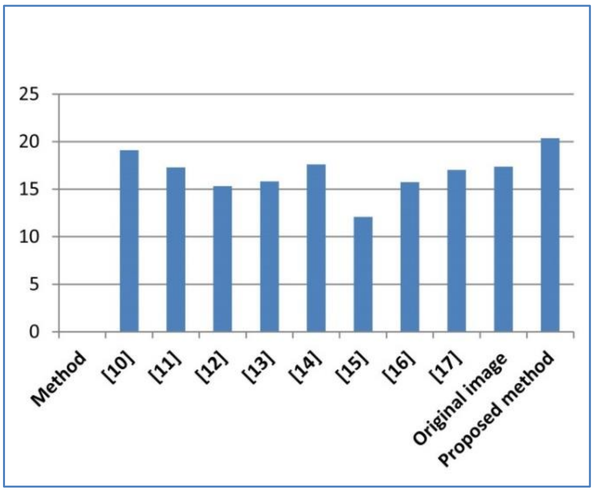

Fig. 6. Comparison of PSNR result with other methods.

SSIM is a metric that quantifies the similarity between patches of an original image and corresponding enhanced patches at specific locations, considering three key aspects: brightness, contrast, and structure. A higher SSIM value indicates a smaller amount of distortion and better overall enhancement [21–22]. In the case of comparing the SSIM scale values of the proposed method with those of other methods, the proposed method does have higher SSIM values compared to [11–17], and almost close to the values of [10], as depicted in Fig. 7. So, the proposed method achieves a higher level of similarity and better improvement in terms of brightness, contrast, and structure.

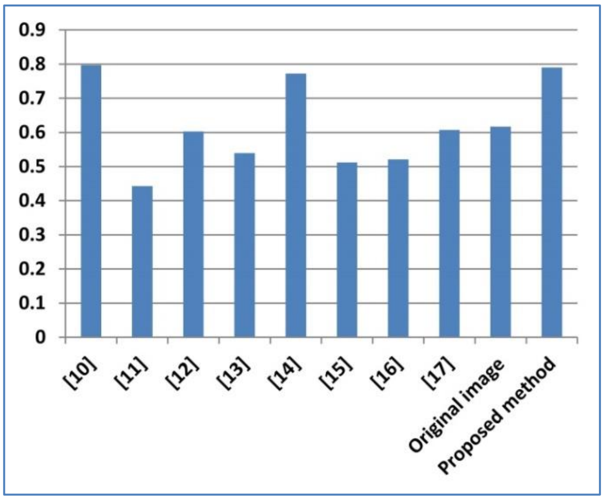

Fig. 7. Comparison of SSIM result with other methods.

V. CONCLUSION

This paper addresses the significant challenges associated with analyzing underwater images, particularly in the context of detecting illicit materials and gathering intelligence for security agencies. Underwater image analysis is inherently complex due to factors such as light transmission in water, degradation of image quality, and limitations in underwater object detection and recognition. To overcome these challenges, an enhancing approach is proposed to enhance underwater images. Experimental results demonstrate the effectiveness of the proposed approach when evaluated using MSE, PSNR, and SSIM metrics. It outperforms several alternative methods in terms of MSE, achieves higher PSNR values compared to other methods, and obtains higher SSIM values, indicating better similarity and enhancement. These results support the effectiveness and superiority of our approach in improving the image and the possibility of using it in practical applications.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Hesham Hashim Mohammed and Shatha A. Baker worked on the code's implementation and designed the numerical experiments. Omar Ibrahim Alsaif oversaw the entire production and supplied ideas for the paper. All authors wrote the paper and approved the final version. All authors had approved the final version.

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