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Enhancement of Underwater Image by Using Adaptive Attenuation Curve Prior Method

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ABSTRACT: The attenuation (sum of absorption and scattering), which is caused by the dense and non-uniform medium, generally leads to problems of color degradation and detail loss in underwater imaging. In this paper, we describe an enhancement of underwater images by using adaptive attenuation-curve prior method. This method uses color channel transfer (CCT) to preprocess the underwater images, light smoothing, and wavelength dependent attenuation to estimate water light and obtain the attenuation ratio between color channels, and estimates and refines the initial relative transmission of the channel. Additionally, the method calculates the attenuation factor and saturation constraints of the three color channels and generates an adjusted reverse saturation map (ARSM) to address uneven light intensity, after which the image is restored through water light and transmission estimation. Furthermore, we applied white balance fusion globally guided image filtering (G-GIF) technology to achieve color enhancement and edge detail preservation in the underwater images. Comparison experiments showed that the proposed method obtained better color and dehazing effects, as well as clearer edge details, relative to current methods. The evaluation metrics used to know the performance of the developed algorithm are MSE and PSNR.

KEYWORDS: CCT, ARSM, G-GIF

I.INTRODUCTION

Activities performed underwater have been increasing, and given the relatively complicated underwater environment, issues with obtaining images include dim light, noise, color degradation, and loss of detail. Based on the need for high-quality underwater images [1], their restoration and enhancement will allow improvements in advanced marine applications and services. Applications and services, such as underwater archaeology, marine life collection, and underwater monitoring, rely heavily on high-quality underwater images.

Underwater optics is one of the most fundamental parts, and its key is to solve the problem of underwater light attenuation. The underwater light attenuation is caused by scattering and absorption, due to light refraction and dust-like particles floating around in the water, underwater images are always affected by scattering.

The restoration and/or enhancement of underwater images are mainly achieved through two algorithms and/or technologies: image- and physics-based methods. Traditional image enhancement methods, such as white balance, histogram equalization, and contrast-limited adaptive histogram equalization [6], can improve image clarity and color saturation; however, these methods are ineffective for underwater images with complex physical characteristics. Park et al. proposed a comprehensive color model based on histogram stretching [3], and improved the image chromaticity measurement (ICM) method and stretched the input image based on the Rayleigh distribution to preserve the detail in the enhanced area.

The physics-based method comprehensively considers the basic physics and underwater imaging theory of light propagation in water media. Because of the influence of light degradation and scattering, Song et al. proposed a statistical model of background light and combined transmission map [7] optimization to eliminate underwater haze and improve image clarity. Additionally, Chang et al. proposed a single-frame underwater image restoration model based on depth estimation and transmission compensation [8], which solved a series of problems caused by light scattering and absorption.

A recent study combined the blue-green channel and the red channel to create a single underwater image



restoration method that first restores the blue-green channel by de-hazing and then corrects the red channel using the grey world hypothesis theory. Although this established an adaptive exposure image to solve the problems of overexposure and underexposure, it failed to preserve image details. A previous study proposed a detail-preserving underexposed image enhancement [4] method using optimal weighted multi-exposure fusion [10], which effectively preserved the color of the image, whereas another study proposed a super-resolution.

Underwater image enhancement method that optimized the retinex algorithm and then used a neural network to train the Y channel to improve the dynamic range and clarity of the underwater image. However, in both cases, there remained deficiencies in the acquisition of image color features. A previous study proposed a submerged scattering method based on a convolutional neural network (CNN) and used adaptive bilateral filtering to refine the estimation results, followed by a balanced method to eliminate image color differences. Although this method showed advantages in qualitative and quantitative analyses, flaws remained in detail and exposure processing of the image. Additionally, image enhancement methods based on deep learning were developed to eliminate image blur and increase color saturation.

However, the results showed incomplete preservation of edge details. An image restoration method based on the attenuation-curve prior is proposed, which relies on the capability of the color of the clear image to be well approximated by hundreds of different colors, and that the pixels in the same color cluster form a color that represents a power function curve associated with an RGB value.

Another study proposed an underwater scene depth estimation method based on image blur and light absorption and capable of application in an image formation model to restore and enhance underwater images [2]. Additionally, a report proposed a new underwater image restoration strategy involving two different transmission coefficient estimation methods, with one based on optical characteristics and the other dependent on image processing knowledge. Subsequent fusion of the two transmission maps produces a final result that is adaptively weighted through their respective saliency maps, with the obtained signal radiance decomposed by point spread function (PSF) deconvolution and color compensation. With the rapid development of deep learning techniques for image restoration and enhancement, deep learning-based underwater image enhancement methods [5] have been widely used.

One study applied deep sparse non-negative matrix factorization to estimate the illumination of underwater images, thereby ensuring the constancy of image color, and another used the depth map based on CNN estimation to achieve a dehumidification effect of the image and trained it by image equalization. Additionally, a previous study used a super-resolution CNN to solve image blur, and another study applied a multi-scale structure to predict the depth map [9] of a scene to enhance the color of underwater images. Although challenges, such as methods that effectively address issues associated with underwater light scattering and restoration, an enhancement of colors and details of underwater images, remain, the present study is focused on establishing an underwater image database to increase convenience and enhance research efforts.

However, current methods are either inadequate for color enhancement or result in low image definition, especially when edge details in the image are not clear enough and result in a blurred image. A reflected light reaching the camera through an object is shown in Fig. 1. Scattering is a phenomenon caused by light interaction with the medium in water and is divided into backscattering and forward scattering. Backscattering describes the scattering of ambient light according to the line of sight before finally propagating to the image plane, resulting in large reductions in scene contrast.

Forward scattering occurs when part of the reflected light is transmitted at a small angle, it is easy to cause image blur. In this study, we describe the development of an underwater image enhancement method based on adaptive attenuation-curve prior. To improve image quality, we first preprocess the underwater images using color channel transfer (CCT), followed by the estimation of the transmission of each pixel according to the distribution of each pixel on the curve and then the estimation of the attenuation factor to compensate the transmission. We then generated an adjusted reverse saturation map (ARSM) to address issues with image exposure and artificial lighting and used saturation constraints to adjust the transmission of the three color channels to prevent image oversaturation and reduce the noise of each pixel. To achieve color enhancement and preserve edge detail, we used globally guided image filtering (G-GIF) to obtain the best gain factor white balance fusion.



II.EXISTING METHOD

Owing to refraction, absorption and scattering of light by suspended particles in water, raw underwater images have low contrast, blurred details and color distortion. These characteristics can significantly interfere with visual tasks such as segmentation and tracking. In the existing system very deep super resolution reconstruction model (VDSR) is introduced to underwater resolution applications. With it, the Underwater Resnet model is used along with CNN to obtain the feature map. The existing system is not able to remove the background noise, which will reduce the efficiency.

III.PROPOSED METHODOLOGY

An image restoration method based on the attenuation-curve prior is proposed, which relies on the capability of the color of the clear image to be well approximated by hundreds of different colors, and that the pixels in the same color cluster form a color that represents a power function curve associated with an RGB value.

There are many influencing factors in the underwater environment, including dust-like particles in the medium that cause changes in the wavelength-dependent attenuation coefficient. Equation suggests that wavelength. We propose a more efficient prior method (adaptive attenuation-curve prior) that can be used in various complex environments, such as atmospheric fog and low-light underwater areas. We define pixels with similar colors as belonging to the same cluster. For images in a clear atmospheric environment, a previous study verified that hundreds of clusters can represent all of the colors in the image, resulting in more significant outcomes.

In an underwater environment, two factors affect image clarity and changes in the observed image: a change in the distance, $d(x)$, from the camera to the target, which causes differences in transmittance of each pixel, and the wavelength-dependent attenuation coefficient, β_c , that results in differences in the three elements in the transmission vector $[t_c(x)]$. These two factors and Eq. (8) result in attenuation (to different degrees) of scene radiation, $J_c(x)$, from the same cluster (with similar original colors), leading to different captured colors, $I_c(x)$, in the observed image. Because the depth of the camera is different, each pixel value of the cluster is described in the RGB space, and a line will be formed between the pixels starting from the original color, J (if $t = 1$), and ending at the water color, B . This suggests that when $t = 0$, the wavelength-dependent attenuation coefficient will be calculated according to Eq. (10) and referred to as the attenuation-curve (Fig. 2).

We define the RGB coordinate space with water light as the origin; therefore, the pixels observed by the intensity of the green or blue channel ($I_c' - B_c'$) have a power function relationship with the pixels of the red channel ($I_r - B_r$). Because B and $\delta c'$ are constants of underwater scenes, the radiance, J , of the scene is the only dependence of the curve, and different radiances correspond to different curves. Therefore, the degradation process of underwater images can be simulated with attenuation curves and adapted to different underwater environments. Four colors to mark four pixels in the pixel clusters of an image are used in Fig. 2(a), and the four clusters distributed in four different positions are shown in Fig. 2(b). Assuming $B = [0.16, 0.66, 0.58]$, the corresponding model shown in Fig. 2(c) represents the same cluster composite image shown in Fig. 2(a); however, because the scene depth and attenuation coefficients of the three color channels are different, the color of each cluster is different from the original color. The change in the color space is shown in Fig. 2(d).

The main contributions of this article are as follows:

- 1) We developed an underwater image restoration and enhancement method based on adaptive attenuation-curve prior that can simulate the light attenuation process in different underwater scenes and effectively eliminate the effects of image noise, haze, and artificial lighting, thereby allowing image de-blurring, color enhancement, and edge detail preservation;
- 2) We used CCT as a pre-processing operation for image de-hazing, resulting in improved de-hazing effects relative to previous methods;
- 3) For image enhancement, white balance fusion G-GIF enhanced image brightness and color while retaining edge details, thereby improving the visual effect;



4) We demonstrated the efficacy of the method in underwater and low-light environments.

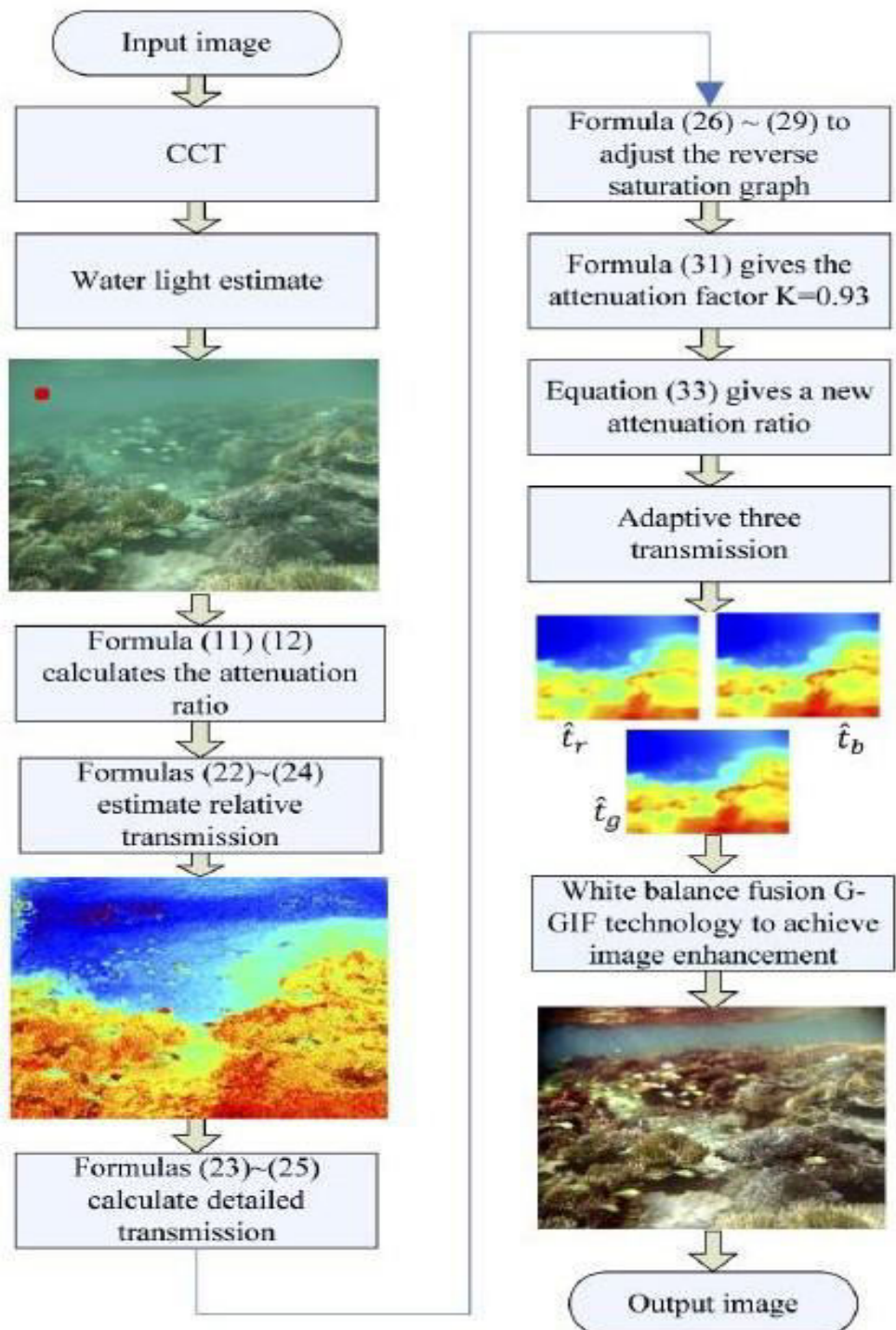


Fig. 1: Block Diagram of Proposed System

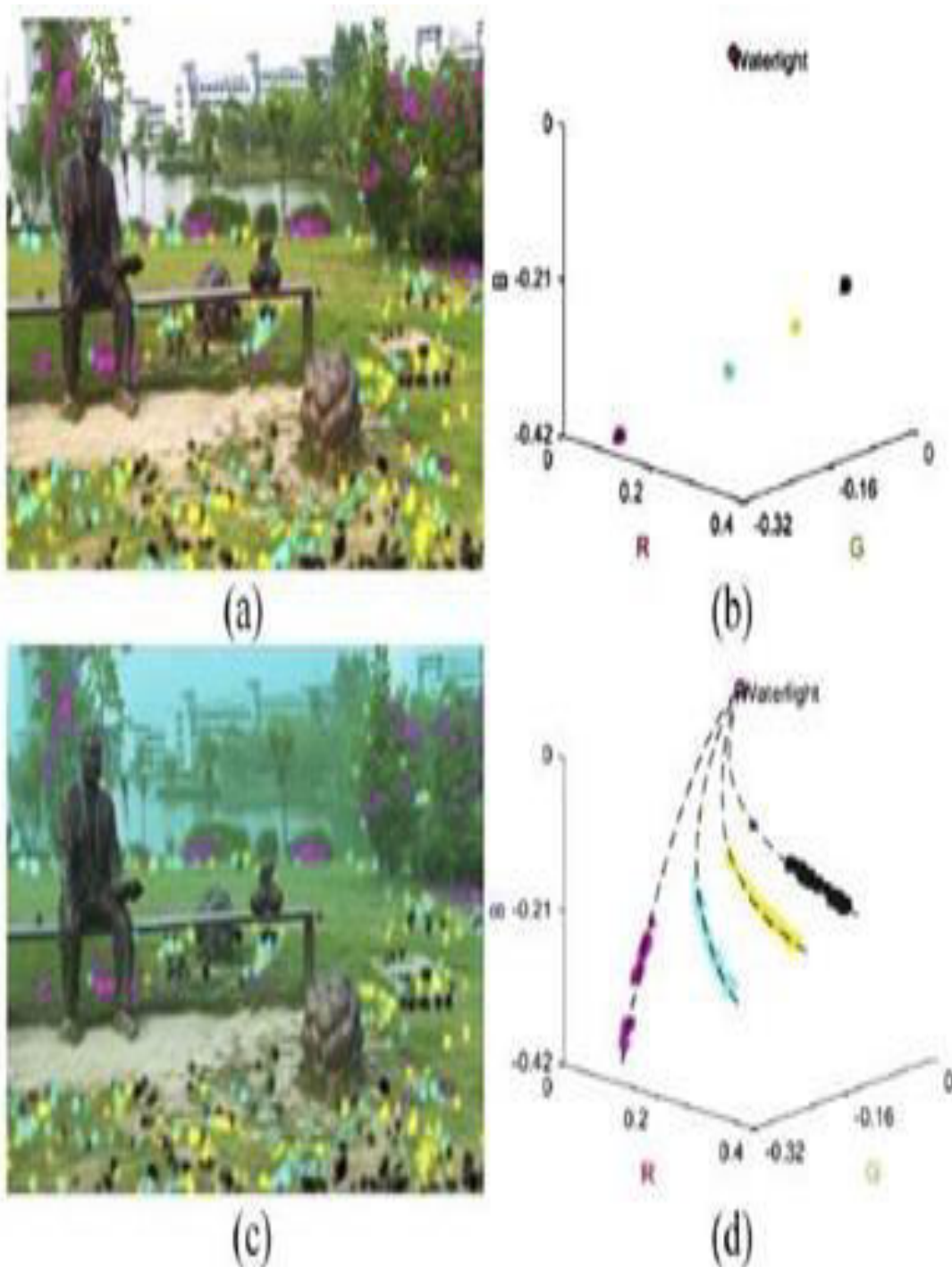


Fig. 2: Decay Curve Priority (a) Clear Pixel Picture (b) Clusters corresponding to different positions in RGB space (c) Composite image of the same clutter (d) The corresponding attenuation-curve in RGB space



IV.RESULTS AND DISCUSSION

	INPUT IMAGE	EXISTING OUTPUT IMAGE	PROPOSED OUTPUT IMAGE
IMAGE 1			
IMAGE 2			
IMAGE 3			
IMAGE 4			
IMAGE 5			

Fig. 3: Comparison of several images between Existing Output Image and Proposed Output Image



The algorithm has been implemented and verified using MATLAB. The evaluation metrics used to know the performance of the developed algorithm are PSNR, MSE and SSIM. Comparison between existing and proposed methods for various evaluation parameters is shown in Table 1, 2 and 3.

INPUT IMAGE	PSNR	
	EXISTING METHOD	PROPOSED METHOD
IMAGE 1	2.99	15.36
IMAGE 2	1.76	16.73
IMAGE 3	2.64	13.14
IMAGE 4	2.72	11.22
IMAGE 5	1.50	10.99

Table 1: Comparison of PSNR value in Existing and Proposed Method

INPUT IMAGE	MSE	
	EXISTING METHOD	PROPOSED METHOD
IMAGE 1	64.72	19.15
IMAGE 2	58.75	13.77
IMAGE 3	43.46	17.49
IMAGE 4	47.68	20.89
IMAGE 5	50.21	25.64

Table 2: Comparison of MSE value in Existing and Proposed Method

INPUT IMAGE	SSIM	
	EXISTING METHOD	PROPOSED METHOD
IMAGE 1	0.56	0.68
IMAGE 2	0.62	0.71
IMAGE 3	0.53	0.72
IMAGE 4	0.58	0.64
IMAGE 5	0.59	0.66

Table 3: Comparison of SSIM value in Existing and Proposed Method

Table 1, 2 and 3 shows the comparison of evaluated parameters for existing method histogram equalization and proposed method enhancement of underwater images by using very deep super resolution. From this we can conclude that the above technique provides the best outcome not including loss of disparity and dispersion of the original image, and moreover it eliminates the fog in the remote sensing images. Peak signal to noise ratio is often abbreviated PSNR and is defined as the ratio between the utmost probable power of a signal and the power of humiliating noise that influences the reliability of its demonstration. Since many signals have a very broad dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale.

PSNR is simply defined via the mean squared error. MSE is defined as

$$MSE = \frac{\sum_{i=0}^{m-1} \{ \sum_{j=0}^{n-1} \|f(i,j) - g(i,j)\|^2 \}}{m \times n} \quad \dots (1)$$

Here, in $f(i,j)$ signifies the original (reference) image and $g(i,j)$ signifies the dehazed image and i, j are the pixel function of the $m \times n$ picture.

The PSNR is defined as

$$PSNR = 20 \log_{10} \left(\frac{MAXf}{\sqrt{MSE}} \right) \quad \dots (2)$$

Here, MAXf is the maximum possible pixel value of the picture. If the pixels are indicated using 8 bits per sample, then MAXf is 255. If an image is high quality then it has higher PSNR value.

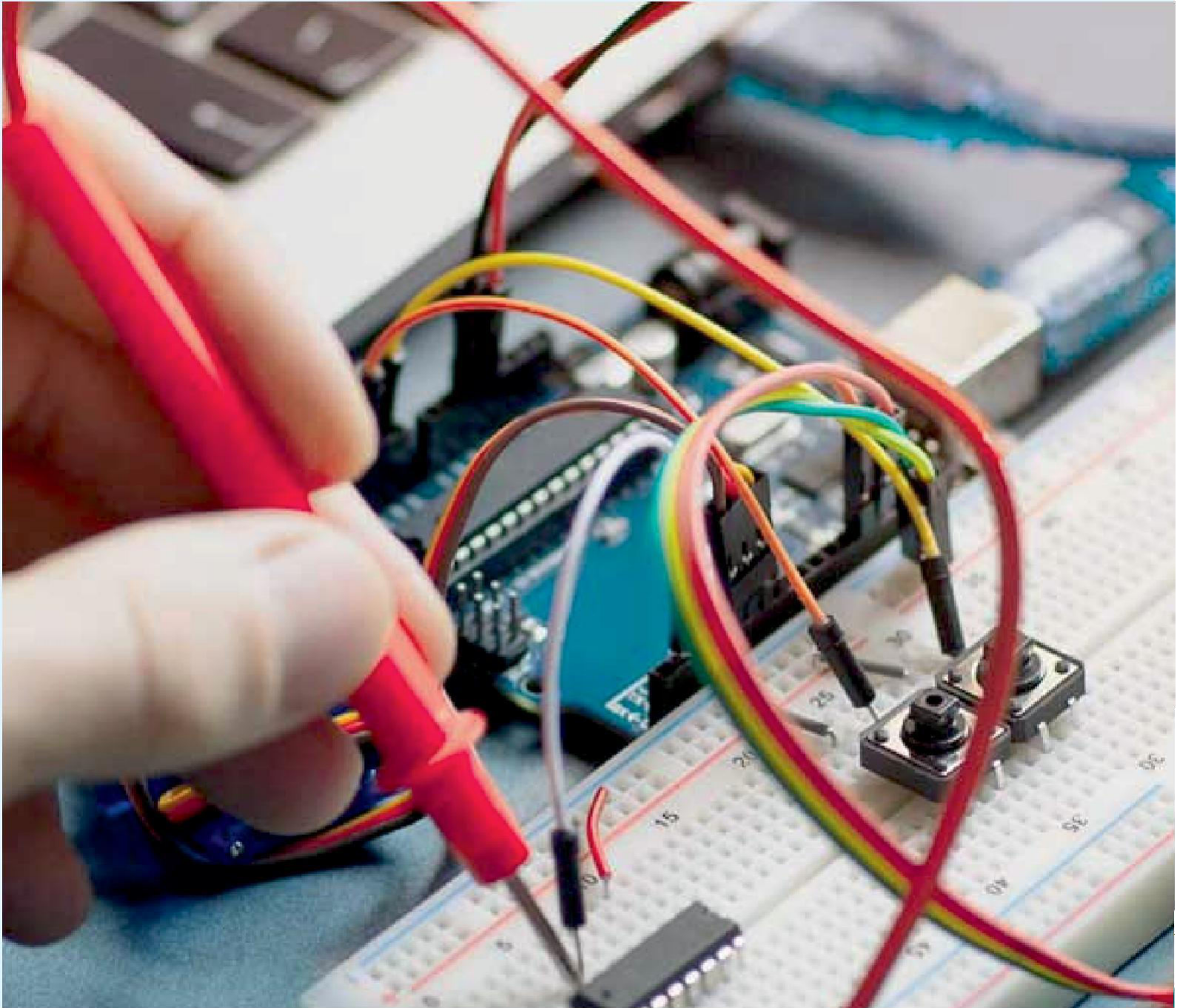


V.CONCLUSION

In summary, we described the development of a method for enhancing underwater images based on an adaptive attenuation-curve prior. Compared with a fixed attenuation-curve method, the proposed method simulated the light attenuation process for different underwater scenes and used smoothness and light attenuation to estimate water light, cluster pixels on the curve according to a priori positions, and estimate the transmission of each curve. Additionally, the attenuation factor and the saturation constraints of the three color channels were then calculated to eliminate image oversaturation and noise and address the problem of uneven light intensity through ARSM. Moreover, we applied white balance fusion G-GIF technology based on the best gain factor to achieve color enhancement, edge detail preservation, and light intensity adjustment. The qualitative evaluation revealed that the proposed method improved image contrast, and adjusted the uniformity of light. Furthermore, the quantitative analysis indicated that the proposed method outperformed other methods. Our future work will focus on improving this method to address shortcomings involving scenes in which the light is too dim or too strong.

REFERENCES

- [1]. Y. Wang, W. Song, G. Fortino, L. Qi, W. Zhang, and A. Liotta, "An experimental-based review of image enhancement and image restoration methods for underwater imaging," *IEEE Access* 7, 140233–140251 (2019).
- [2]. M. Mathur and N. Goel, "Enhancement of Underwater images using White Balancing and Rayleigh-Stretching," in 2018 5th International Conference on Signal Processing and Integrated Networks (SPIN), Noida, 924–929 (2018).
- [3]. C. Li, J. Guo, R. Cong, Y. Pang, and B. Wang, "Underwater Image Enhancement by Dehazing With Minimum Information Loss and Histogram Distribution Prior," *IEEE Trans. Image Process.* 25(12), 5664–5677 (2016).
- [4]. S. Park, Y. Shin, and S. Ko, "Contrast Enhancement Using Sensitivity Model-Based Sigmoid Function," *IEEE Access* 7, 161573–161583 (2019).
- [5]. Q. Shen, Y. Yao, J. S. Li, F. F. Zhang, S. L. Wang, Y. H. Wu, H. P. Ye, and B. Zhang, "A CIE Color Purity Algorithm to Detect Black and Odorous Water in Urban Rivers Using High-Resolution Multispectral Remote Sensing Images," *IEEE Trans. Geosci. Remote* 57(9), 6577–6590 (2019).
- [6]. A. S. A. Ghani and N. A. M. Isa, "Automatic system for improving underwater image contrast and color through recursive adaptive histogram modification," *Comput. Electron. Agricult.* 141, 181–195 (2017).
- [7]. W. Song, Y. Wang, D. Huang, A. Liotta, and C. Perra, "Enhancement of Underwater Images with Statistical Model of Background Light and Optimization of Transmission Map," *IEEE Trans. Broadcast.* 66(1), 153–169 (2020).
- [8]. H. Chang, C. Cheng, and C. Sung, "Single Underwater Image Restoration Based on Depth Estimation and Transmission Compensation," *IEEE J. Oceanic Eng.* 44(4), 1130–1149 (2019).
- [9]. C. Li, J. Quo, Y. Pang, S. Chen, and J. Wang, "Single underwater image restoration by blue-green channels dehazing and red channel correction," in *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, Shanghai, 1731–1735 (2016).
- [10]. S. Liu and Y. Zhang, "Detail-Preserving Underexposed Image Enhancement via Optimal Weighted Multi-Exposure Fusion," *IEEE Trans. Consumer Electron.* 65(3), 303–311 (2019).



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