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A REVIEW ON UNDERWATER IMAGE ENHANCEMENT TECHNIQUES

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***Abstract*—Underwater imaging is an innovative research area that has more benefits to researchers and scholars for mine detection, navigation, autonomous underwater imaging devices, etc. Underwater photos suffer greatly from scattering, light absorption, color cast, and the presence of artifacts, which causes the image to become increasingly blurry. At this juncture, color correction and image enhancement are highly recommended for getting a precise image with the right information. This paper summarizes the recent algorithms and their approaches in the area of underwater imaging enhancement techniques. An outline of the developing applications of underwater image processing is also presented.**

***Index Terms*—Color Correction, Dehazing, Image Enhancement, Underwater Imaging.**

I. Introduction

In recent times, researchers eagerly want to explore the enigmatic underwater world. Examining underwater imaging is highly significant for various purposes such as exploring ocean resources, conducting marine ecological research, monitoring deep-sea installations, and utilizing naval military applications. In the fast-growing era of modern technology, underwater image processing opens a broad spectrum of areas for future research and innovation. A considerable quantity of studies going on toward the restoration and enhancement of underwater images. The objective of this study is to conduct a comprehensive survey of the different techniques investigated in the field of enhancing underwater images.

Underwater image processing is one of the prominent areas that process digital images using digital computers. It facilitates a wide range of innovations that can handle the image by eliminating unwanted data due to the scattering and absorption of light through water. Image generation, enhancement, and restoration are the basic three subsections that come under image processing. The generation section is associated with the identification of the project and examine the image whereas enhancement is the area in which the features like contrast, brightness, and hue are upgraded. Eliminating the undesired component from the underwater image deals with the restoration process. Underwater imaging is a digital way to easily identify the details and objects on the sea floor within a short time. Underwater imaging even has been more prominent since the early 2000s. The initial stages of the underwater image processing are described in Fig. 1.

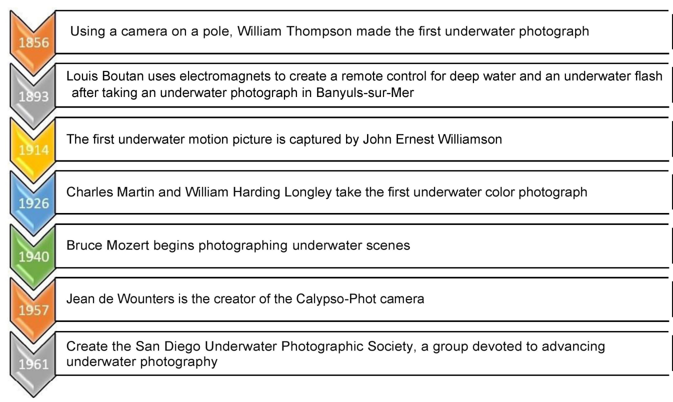

Fig. 1. Initial steps of Underwater Image Processing

Generally, reduction in the clarity of underwater images becomes speedy when the distance exceeds 4-5m from the ground level. Therefore, to increase the depth's visibility, artificial light is required for capturing, which leads to issues like blurriness and distortions. The quality of underwater images can be significantly affected by attenuation. When compared to shorter wavelengths of light, such as blue, longer wavelengths of light, such as red, are absorbed more quickly. This might cause the color balance to shift towards blue or green hues. This paper mainly concentrated on two problem-solving methods: Underwater image restoration and underwater image enhancement techniques. Also, this article summarizes some of the interesting and excellent underwater image processing methods, in which machine-learning techniques overcome the shortcoming of conventional methods to some extent. Convolutional neural network (CNN) and generative adversarial network (GAN) based deep learning methodologies are explained in section III.

In addition, this review analyses the requirements, challenges, and current applications of underwater imaging. The rest of this paper is organized as follows: Section II discusses the basics of the underwater imaging model. Section III summarizes different underwater image enhancement and restoration techniques. Section IV explains some of the details of the underwater image datasets. Section V gives an outline of the existing applications and upcoming facilities and the conclusion is presented in Section VI.

II. UNDERWATER IMAGING MODEL

Underwater image enhancement techniques support the development of human activities like autonomous underwater vehicles, underwater object grabbing, and real-time navigation that rely on high-resolution and high-quality underwater photographs. Based on the most popular three-component underwater imaging model [1], the overall energy $E_T(x,y)$ recorded by the camera is described as the additive sum of the direct luminance element, forward scattering element, and background scattering element.

$$E_T(x,y) = E_d(x,y) + E_{fs}(x,y) + E_{bs}(x,y) \quad (1)$$

$E_d(x,y), E_{fs}(x,y)$, and $E_{bs}(x,y)$ indicate the direct luminance, forward scattering, and background scattering elements respectively. The distance between the camera and the underwater scene is typically large, and the effect of the forward scattering element can be disregarded. Therefore,

$$I_\lambda(x,y) = J_\lambda(x,y)T_\lambda(x,y) + B_\lambda(1 - T_\lambda(x,y)) \quad (2)$$

where λ is either R, G, or B. $I_\lambda(x,y)$ and $J_\lambda(x,y)$ represent the underwater image captured by the camera and its improved version. $T_\lambda(x,y)$ and B_λ represents the transmission map and global background light. Deep learning techniques have recently been widely used by researchers to improve underwater image quality. In addition, complex model construction and parameter selection can be avoided using an end-to-end network.

III. UNDERWATER IMAGE ENHANCEMENT AND RESTORATION TECHNIQUES

Underwater images are usually expressed as low contrast and fuzzy detailing because of light dispersion and absorption. Enhancement and restoration procedures can either be done by conventional methods or machine/deep learning algorithms. Fig. 2. illustrates the degraded and enhanced underwater images. The paper [2]-[7] explains some of the popular conventional underwater image enhancement and restoration techniques. The documents [8]-[10] and [12]-[27] describe machine learning algorithms in which convolutional neural networks (CNN) based methods are presented in [8]-[10] and [12]-[19] and generative adversarial network (GAN) models are described in [20]-[26]. The paper [27] introduced a real-time and unsupervised advancement scheme (RUAS) for underwater computer visuals in natural light situations.

(a) (b)

Fig. 2. Underwater images : (a) Degraged (b) Enhanced [2]

The article [2] introduced a color filter array (CFA) based color correction method and retinex-based enhancement approach. Also, discussed an adaptive linear histogram processing for underwater photos with distorted color bias. In [3], the authors present a single underwater image enhancement method with two stages: an upgraded white balancing method and an artificial multiple under-exposure fusion scheme. White balance and variational contrast-based hybrid frameworks were proposed in [4] for the enhancement of underwater visuals. Greater compensation was achieved by integrating the underwater white balance (UWB) algorithm with histogram stretching.

In the paper [5], W. Luo et al. introduced a fusion approach in which color balance, contrast optimization, and histogram stretching algorithms were constituted. A manually defined background lights (MABLs) database was developed and using underwater picture restoration and color correction for modeling an efficient underwater image enhancement technique [6] was demonstrated for underwater visuals. In this paper [7], Ancuti et al. explained a single-image approach that doesn't need any specialized hardware or knowledge of the underwater environment. The comparison results of conventional underwater image processing techniques are briefly described in Table I.

The authors, K. Wang et al. submitted a unique method of the joint network to improve color correction and dehazing over numerous iterations in the article [8]. The properties of the underwater imaging model and structure decomposition based on a two-stage underwater image convolutional neural network (UWCNN-SD) were proposed in [9]. In addition, the paper [10] introduces a two-stage progressive distortion approach consisting of horizontal and vertical distortions influenced by the Chiang and Chen [11] physical model. The paper [12] explains an underwater image enhancement model using Deep Learning (DL) techniques and the results show the

TABLE I
COMPARISON OF CONVENTIONAL UNDERWATER IMAGE PROCESSING TECHNIQUES

REF. NO.	AUTHORS	METHOD	DATASET	EVALUATION METRICS	RESULTS
[2]	Changli et al.	Retinex-based chroma correction and enhancement technique using color filter arrays [CFA] and adaptive linear histogram conversion.	UIEB	Entropy-7.73 NIQE-3.57 UCIQE-0.48 UIQE-4.39	This method produces images with crisper elements and better color-correction outcomes.
[3]	Ye et al.	A method for improving underwater visual appearance without the need for additional information beyond the input scenes.	UIEB	UIQM-5.47 UCIQE-0.63	The technique successfully improves the picture quality of underwater scenes in real-world, low-light, and foggy conditions.
[4]	Xinjie et al.	A fusion improvement approach for underwater images that incorporates underwater white balance, variational contrast, and saturation.	UIEB	UIQM-1.53 PCQI-1.23 UCIQE-0.63 MEON-22.91	The framework can render colors more accurately and improve visibility.
[5]	Weilin et al.	A fusion approach for improving underwater scenes that includes histogram extending contrast adjustment, and color balance.	RUIE	UCIQE-0.58 PSNR-14.95	Higher PSNR and UCIQE metric values and better results in terms of strength and capacity.
[6]	Wei et al.	An effective method for underwater picture enrichment for applications like color correction and image restoration.	UIEB	SSIM-0.81 UCIQE-0.54 Entropy-7.99	Enhanced the color and contrast of different underwater scenes.

algorithm can learn how to optimize the underwater visuals. An end-to-end deep network for underwater scene reconstruction was established in [13] and the network includes two sections namely a channel-wise color feature extraction and a dense-residual feature extraction.

The UIE-Net modeled on CNN was introduced in [14] and was concerned with removing the haze and color retouching tasks. A deep residual framework-based underwater image enhancement solution was presented in [15], the article gives an idea about the impact of batch normalization. A three-stage convolutional neural network (CNN) structure was suggested in [16], inspired by the unique properties of inter-channel correlation and distorted color visuals. In the paper [17], S. Song et al. presented a new method for recognizing underwater creatures and combines the MSRCR image enhancement algorithm and Mask R-CNN. In the journal [18], a CNN-based method was developed without the need for real-world scenes, and a Deep Differential Convolutional Network for single-scene super-resolution was developed in the article [19]. The comparison of the CNN-based underwater image processing models are explained in Table II.

In the paper [20], the authors mainly concentrated on the solution for the problem associated with retrieving the data and enhancing the minutiae while trying to eliminate the artifacts. So, the paper designed a spiral GAN which can accurately recover the real-world underwater image with perfect contrast and vivid features. Real-time underwater image enhancement using a conditional generative adversarial network model [21] was proposed.

For the monocular underwater image color correction procedure, a generative adversarial network-WaterGAN [22] was presented for achieving practical underwater visuals from in-air visuals and depth pairings in an unsupervised pipeline manner. The method [23] was for learning to convert images from one domain to another without the need for paired samples. Using Generative Adversarial Networks (GANs), the research [24] suggests a technique to enhance the visual quality of underwater sceneries to enhance input to vision-driven behaviors later on in the autonomy pipeline.

To solve the challenges using generative adversarial networks (GAN), the article [25], X. Chen et al. provided a GAN-based restoration approach (GAN-RS). A multiscale dense generative adversarial network (GAN) was explained in [26] for avoiding color distortion, underexposure, and fuzz issues. In [27], the authors achieve improved underwater machine vision through real-time and unsupervised advancement schemes, RUAS. The comparison results of the generative adversarial network-based underwater image enhancement and restoration approaches are briefly described in Table III.

TABLE II
COMPARISON OF CNN-BASED UNDERWATER IMAGE PROCESSING TECHNIQUES

REF. NO.	AUTHORS	METHOD	DATASET	EVALUATION METRICS	RESULTS
[8]	Kun et al.	A collaborative platform to enhance the outcomes of color correction and dehazing after several iterations.	UIEB, EUVP, and UFO-120	PSNR-29.94 SSIM-0.94	Accurate results can be obtained by using the joint optimization, dehazing, and color correction modules.
[9]	Ting et al.	A two-stage CNN underwater visual based on underwater imaging characteristics and structural decomposition (UWCNN-SD).	U45	UIQM-5.11 UCIQE-0.61	According to the study of fabricated, real-world photos and films, the proposed UWCNN-SD technique can improve underwater visuals.
[10]	Yufei et al.	A two-stage approach for repairing both vertical and horizontal distortion in underwater scenes.	Synthetic and Real-world underwater images	PSNR-27.45 SSIM-0.92 UIQM-5.35	Higher PSNR, SSIM, and UIQM evaluation metric values can be produced by the network.
[12]	Amit et al.	A deep CNN for underwater visual reconstruction that takes into account the damaged underwater visions and extracted contexts.	EVUP	RMSE-6.02 SSIM-0.83 PSNR-29.5 UCIQE-0.31 UIQM-0.67	The model performs better than other state-of-the-art techniques while accurately enhancing photos.
[13]	Akshay et al.	An end-to-end deep network for underwater visual reconstruction.	Synthetic underwater scenes	BRISQUE-20.69 PSNR-27.84 UIQM-4.22 SSIM-0.86	To retrieve the robust color features and to alleviate underwater haze effects as well as image blurriness, respectively, the channel-wise color feature extraction module and dense-residual feature extraction module are used.

IV. UNDERWATER IMAGE DATASET

The Monterey Bay Aquarium Research Institute prepared MBARI underwater scene database (Yang et al. 2019) and it includes 666 visuals of fishes. This database is available in [28].

Three distinct subsets comprise the Real-world Underwater Image Enhancement (RUIE) dataset (Liu et al. 2020). The RUIE dataset contains roughly 4000 pictures of sea urchins, sea cucumbers, and scallops. In [29], the RUIE dataset can be accessed.

The SQUID (Stereo Quantitative Underwater Image dataset) was made up of 57 stereo pairs from four different locations in Israel, two in the Red Sea, which shows tropical water, and the remaining two in the Mediterranean Sea, which indicates temperate water (Berman et al. 2020).

An Underwater Image Enhancement Benchmark (UIEB) of 950 underwater photos was created by Li et al. These underwater images taken in the real world have relevant reference labels for 890 of them.

Islam et al. (2020) proposed the Enhancement of the Underwater Visual Perception (EUVP) dataset, which contains both paired and unpaired collections of underwater photos. In [30], this EUVP dataset is available.

V. APPLICATIONS OF UNDERWATER IMAGE PROCESSING

According to personal as well as scientific research, underwater imaging plays a unique role in giving a clear idea about the underwater environment and the availabilities of sustainable resources. Due to the rising demand, various techniques and algorithms are introduced nowadays. The color correction and enhancement methods can generate an excellent image with alleviated noise. This section describes various applications of underwater image processing.

In the underwater navigation field, to explore the environment by collecting and analyzing the data to find the targets. The cleared or enhanced underwater images are used to decide the obstacle location suitably. So, this can reduce the operating cost of the vehicle. The main task of the drivers is to control the machines to retrieve the necessary data. Image registration

TABLE III
COMPARISON OF GAN-BASED UNDERWATER IMAGE PROCESSING TECHNIQUES

REF. NO.	AUTHORS	METHOD	DATASET	EVALUATION METRICS	RESULTS
[14]	Yang et al.	An end-to-end CNN-based framework, UIE-Net for underwater vision improvement.	Synthetic underwater scenes	Entropy-7.57 PCQI-1.23	The model's subsections for improving underwater picture contrast are CC-Net and HR-Net, and they can effectively perform convergent speed as well as accuracy.
[15]	Peng et al.	An extensive residual model for UIE, synthetic scenes generated by Cycle-GAN and VDSR considered for performing underwater resolution applications.	Synthetic underwater scenes	PSNR-41.79 SSIM-0.84	Performing vision-based underwater tasks like segmentation and tracking, the techniques can significantly improve the visual impact of underwater photos.
[16]	Kai et al.	A three-stage convolutional neural network (CNN) structure was developed for underwater visual restoration tasks.	SIDD WED-NEWCLIC	PSNR-30.37 MS SSIM-0.84	Rebuilding the R, G, and B channels take place during the first two stages and the evaluation analysis demonstrates that the approach can work in the real world also.
[20]	Han et al.	A novel spiral generative adversarial framework, Spiral-GAN.	RUIE, EUVP and URPC	UICM-2.85 UIConM-0.73 UIQM-4.62	The network is capable of converting underwater photos of varied qualities into clear visuals with more vibrant colors and features. A study on ablation was also done to evaluate the methods.
[21]	Xai et al.	AA conditional generative adversarial network-based model for real-time underwater visual improvement.	EUVP	SSIM-0.88 PSNR-21.92	The model generates a sizable dataset for supervised learning and formulates a perceptual loss function. Also, evaluate the effectiveness in improving underwater object detection and saliency prediction.

and inter-image motion are the two limitations of localization and the real-time position approach.

In the detection, the equipment retrieves the data from the underwater environment and sends the information to an on-store station through underwater cables. Temperature, salinity, pressure, and underwater scenes can be identified by the sensor-based monitoring system. The methods are mainly used to detect objects: range gating, laser line scanning, modulation technique, multiple perspective image construction, etc.

In short, underwater images have a great role in the study of the underwater area which helps in mine detection, diver visibility, etc. Underwater images are commonly used in pattern recognition, processes like underwater image segmentation, edge detection, and all.

VI. CONCLUSION

The color correction and enhancement procedures of underwater imaging play a prominent role in developing and exploiting the underwater environment. This review summarized recent research works and technological implementations for enhancing underwater images. The first half explained a clear concept of the underwater imaging model, followed by a discussion of enhancement and restoration techniques. Both of these aspects are very helpful for researchers and scholars seeking to gain knowledge about underwater imaging. The most commonly used underwater image datasets were briefly presented. Several metrics that measure the quality of underwater images for quantitative evaluation are thoroughly presented in tables. The final section includes an outline of the applications of underwater imaging in the modern technological world.

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