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A Review of Underwater Image Enhancement and Restoration Techniques Based on Gan

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Abstract. In recent years, underwater image enhancement and restoration technology have significantly contributed to the efficiency of marine operations and the advancement of seabed resource development, which carries substantial academic significance and practical value. This study initially investigates and assesses the underwater imaging model based on the principles of underwater imaging, emphasizing the challenges and issues faced by current technology. Secondly, it thoroughly presents the pertinent research on underwater image enhancement and restoration technologies utilizing generative adversarial networks, and provides an in-depth classification and analysis of the prevailing underwater image enhancement and restoration techniques based on GAN. The study of experimental findings highlights the peculiarities of various classification methods. Thirdly, it summarizes the commonly used datasets and evaluation indicators. Finally, it forecasts and examines the viable development pathways for underwater image enhancement and restoration technology moving forward, particularly emphasizing the significant potential and application value of generative adversarial networks within this domain.

1 Introduction

Land resources have been extensively exploited by humans, resulting in severe resource depletion. Consequently, people have turned their attention to the utilization of marine resources. The ocean covers approximately two-thirds of the Earth's surface and contains abundant resources. The exploitation of marine resources holds significant importance for the development of all countries worldwide. Underwater image enhancement and restoration techniques are of vital significance for the exploration of marine resources [1].

In 2022, Haifeng Yu and colleagues introduced a GAN-based approach for enhancing underwater vision and assessing defogging. This method attained satisfactory outcomes in underwater video enhancement experiments [2]. Huipu Xu et al. proposed a non-paired supervised underwater image enhancement method based on generative adversarial networks. This approach does not require paired image training and performs well in the majority of underwater application scenarios [3].

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In September 2023, Shiwen Li et al. presented a two-stage underwater image restoration technology based on generative block networks and optical models. This method can better accentuate image details and effectively enhance the visual effect of the image [4]. Danilo Avola and colleagues introduced a model for underwater image enhancement that utilizes a real-time generative adversarial network. This model utilizes convolutional neural networks to handle visual data. The network now adopts a supervised mode, enabling the structure and details of underwater images to be preserved [5]. Yinghui Zhang et al. proposed an innovative unsupervised learning-based underwater image enhancement framework. They developed a structure-frequency-aware regularization method that reduces detail loss from numerous spatial frequency aspects and trains quicker than cycle consistency [6].

Chereddy Spandana and colleagues introduced a method for underwater image enhancement and restoration utilizing a cycleGAN approach. The generator in this method incorporates a content loss regularization function, which can preserve the information of low-resolution images in the generated clear images [7]. Naresh Kumar et al. introduced a deep learning-based technique for enhancing underwater images. Four convolutional neural network-based models were trained using the GAN-enhanced dataset and UIEB [8].

In 2024, Yiming Li and colleagues introduced a multi-scale attention conditional generative adversarial network aimed at enhancing underwater images. This method performed well in all indicators, and the generated images did not exhibit obvious over-enhancement or over-saturation [9]. Lingyan Kong et al. introduced a two-stage asymmetric CycleGAN for underwater picture enhancement, effectively resolving challenges related to difficult image enhancement and overexposure in various underwater conditions [10]. Guangtai Zhang and colleagues introduced an enhanced CycleGAN approach, by adjusting CycleGAN, a dataset specifically for image restoration was constructed. This method outperformed existing techniques in both peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM) [11].

This paper begins by presenting the underwater optical imaging model and examines the primary factors that contribute to the degradation of underwater images, as well as the challenges associated with underwater imaging, through the lens of imaging principles. It subsequently outlines the fundamental framework of generative adversarial networks and their utilization in computer vision. It compares and introduces the characteristics of underwater image datasets for underwater image enhancement. At the end of the article, it looks forward to the challenges and future development directions of underwater image enhancement technology based on GAN.

2 Principles of Underwater Imaging

Influenced by factors such as the wavelength of light, light intensity, water flow velocity, water temperature, salinity, particles, and the refraction of light by particles, photographs taken underwater typically exhibit issues such as color distortion, blurring, and low contrast, thereby significantly deteriorating image quality. Therefore, the principle of underwater imaging is of great importance for the study of various image enhancement and restoration techniques.

2.1 Underwater Imaging Model

McGlamery proposed a model for optical imaging in underwater environments [12], as depicted in Figure 1. The light received by the imaging equipment in the underwater environment is composed of direct components, forward scattering components, and backward reflection components. The refraction of light and the influence of suspended particles on light imaging will have an effect.

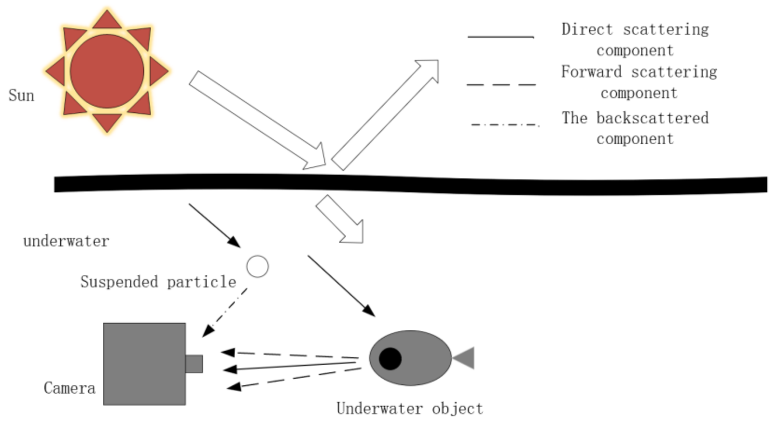

Figure 1. Model for Underwater Optical Imaging(Picture credit: Original)

The direct component illustrated in Figure 1 pertains to the light reflected from the photographed object that directly enters the camera; the forward scattering component consists of light reflected by the object after solar illumination, which deviates from its original trajectory and is randomly captured by the camera; the backward scattering component pertains to light reflected by particles in the water. The image obtained by the camera comprises the aforementioned three light components, thereby differing from the image captured in the atmosphere.

If the object is photographed at a close distance underwater, the impact of the forward scattering component on imaging is minimal. The image is primarily influenced by the backward scattering component. Consequently, the underwater imaging model can be expressed as Formula (1).

$$I(x) = J(x)t_c(x) + B_c(1 - t_c(x)) \qquad (1)$$

Wherein, $I(x)$ denotes the original image, $J(x)$ indicates the clear image, $J(x)t_c(x)$ represents the direct component, $B_c(1 - t_c(x))$ represents the backward scattering component, B_c represents the underwater ambient light, and $t_c(x)$represents the scene light transmittance.

Apart from the scattering phenomenon, the water medium also exerts an influence on imaging. With the increase in depth underwater, red light vanishes first, followed by orange, yellow, green, and blue. Consequently, most underwater images present as green or blue, as depicted in Figure 2.

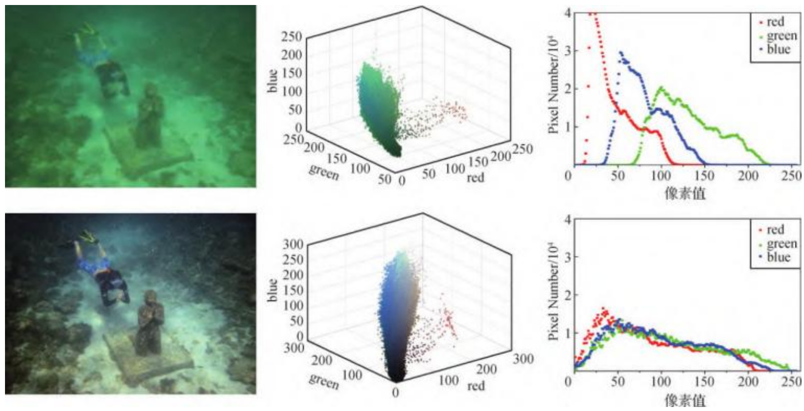

Figure 2. Low- and high-quality underwater picture 3D color distribution and RGB histograms [13].

2.2 Difficulties and Challenges in Underwater Imaging

Subaqueous imagery is essential in the investigation and utilization of undersea habitats' potential. Nonetheless, the present research on underwater imaging encounters various obstacles and hurdles, in addition to the intrinsic phenomena of light scattering and absorption within the aquatic medium.

Firstly, the acquisition of underwater photos necessitates rigorous environmental conditions. The quality of underwater photos captured using natural light is considerably influenced by weather conditions. For example, during typhoons and intense rainfall, the aquatic media is significantly affected by the weather, resulting in obscured underwater photos and diminished image quality.

Secondly, the brightness of underwater images obtained with the aid of artificial light sources is uneven. The natural light that is present in the undersea environment is rapidly diminished, which is the reason why people adopt the method of introducing artificial light sources for the acquisition of underwater images. However, artificial light sources are uneven, presenting bright spots in the center of the image, while the light sources around are conspicuously insufficient in contrast.

Finally, macroscopic particles in water give rise to random noise. There are a considerable number of macroscopic particles in water (such as plankton, some suspended particles like microplastics, microorganisms in water, and dissolved organic matter), which move randomly, intensifying the influence of light scattering on underwater imaging and causing more random noise in underwater images.

3 Basic Structure of Generative Adversarial Networks

GANs constitute an innovative framework grounded in Convolutional Neural Networks (CNNs), exhibiting considerable capacity for ascertaining high-dimensional information from feedback. It is a generative model comprised of two CNN modules: the generator and the discriminator. The predominant architecture of neural networks is for learning from datasets, which frequently results in challenges like classification inaccuracies and overfitting. Nonetheless, GANs provide a formidable architecture featuring self-generating and self-learning elements, capable of surmounting the constraints of conventional networks [3].

3.1 The proposal of Generative Adversarial Networks

The study paper by Goodfellow et al. (2014) characterizes the GAN, represented by the function value $V(D, G)$ [14]. The comprehensive mathematical formulation presented by Goodfellow is illustrated in Formula (2).

$$V(D,G) = E_{xpdata(x)}^{[\log D(X)+E_{zp(z)}^{[\log(1-D(G(z)))]}]} \tag{2}$$

In 2015, a novel variant of the GAN was introduced. The GAN consists of two primary components: the generator and the discriminator.

3.2 Basic Structure of Generative Adversarial Networks

The deep learning framework of the generative adversarial network primarily has two components: the generator and the discriminator. The generator functions as an unsupervised model within the GAN, creating novel values from the input distribution by summarizing the actual input variable distribution. The generator produces a fixed-length random vector derived from the Gaussian distribution, with its construction illustrated in Figure 3.

The discriminator is a supervised GAN model that utilizes category labels alongside input and shared variables. The discriminator receives input values from both the real and produced data sets, categorizing the data as either fake or real accordingly [15]. The discriminator's construction is illustrated in Figure 4.

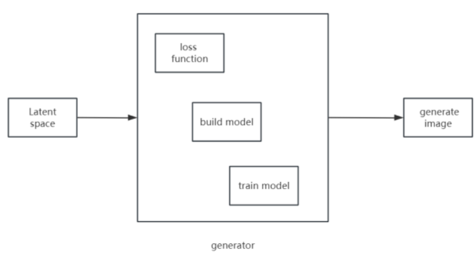

Figure 3. Generator Structure (Picture credit: Original)

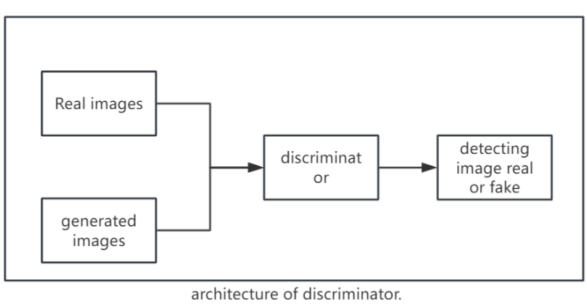

Figure 4. Discriminator Structure (Picture credit: Original)

4 Underwater Image Enhancement and Restoration Method Based on GAN

In recent years, the swift advancement of artificial intelligence technology has led to significant progress in underwater picture augmentation and restoration through generative adversarial networks. This technique has exhibited exceptional efficacy in picture production and style transfer. GAN, with data-driven training techniques, can more effectively address issues resulting from numerous variables.

4.1 The Development History of Underwater Image Enhancement and Restoration Technology Based on Generative Adversarial Networks

Liquan Zhao and colleagues have recently introduced a GAN that incorporates multi-scale and attention techniques for the enhancement of underwater images. The generator network employs a residual convolutional module alongside a multi-scale dilated convolutional module to extract texture and edge information from underwater images, facilitating the capture of underwater features across different scales. In the adversarial network, a multi-scale feature extraction module was developed to improve feature extraction capabilities, and the experimental results shown outstanding performance in both qualitative and quantitative assessments [16]. Fei Fan Yao separately proposed a study on the perception of marine organism images via a diffusion generative GAN network, effectively establishing a model to mitigate the unique optical features of aquatic environments and incorporating a perceptual loss model [17]. Table 1 lists diverse GAN techniques for underwater image enhancement, together with their respective datasets and the assessments and analyses of the experimental outcomes.

Table 1. Summary of Underwater Image Enhancement and Restoration Techniques Based on GANs

Literature	Method Description	Experimental dataset	Analysis and Evaluation
[9]	Multi-scale Attention Conditional GAN	The RUIE dataset was utilized, and 100 underwater images without ground truth were randomly selected from the Internet for subsequent testing.	It is capable of generating satisfactory visual effects, without apparent over-enhancement and over-saturation phenomena.
[10]	Two-stage CycleGAN-based underwater picture enhancing technique	Initially, execute unsupervised learning on the unmatched URC dataset, followed	The image quality, color deviation, and perceptual effect have all been enhanced.

		by supervised training on the paired UIEB dataset.	
[11]	A method for enhancing underwater images using an improved CycleGAN approach	From the UIEBD dataset, 800 images were chosen as Training Set A, and the corresponding 800 reference images as Training Set B. The challenging subset was employed as the test set.	It outperforms the existing technologies in qualitative and quantitative analysis, enhancing visual clarity and system reliability.
[16]	A generative adversarial network employing multi-scale and attention mechanisms for the enhancement of underwater images.	The UIEB dataset	It more accurately represents authentic underwater photos, exhibiting enhanced color fidelity, superior clarity, and improved contrast.
[17]	Investigation of Visual Perception Augmentation for Marine Organism Imagery Utilizing Diffusion Generative Adversarial Networks	The SA dataset and the T dataset, both with a resolution of 256×256, comprise 9,366 images.	DifSG2-CCL can effectively reconstruct specific marine organism images in different datasets, and DP-SG2 enhances perceptual similarity.

4.2 Variants of GAN

4.2.1 Deep Convolutional GAN(DCGAN)

In 2015, Radford et al. proposed the DCGAN hierarchical model. In this model, they presented two convolutional neural network models, namely the discriminator and the generator, with the generator containing a deconvolutional layer, as shown in Figure 5.

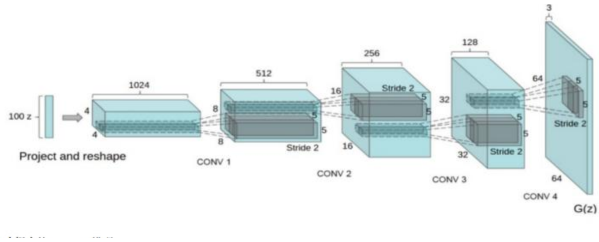

Figure 5. DCGGAN Model [18]

The primary objective of deep convolutional generative adversarial networks is to facilitate unsupervised learning via stride convolution and transposed convolution. Deep convolutional generative adversarial networks have made significant contributions in data augmentation, improving the accuracy of target convolutional neural network models by expanding the dataset size or constructing training models. The combination of deep convolutional GANs with models of convolutional neural networks or established techniques is significant, such as self-learning support vector machines, can yield enhanced accuracy [18].

Conditional Generative Adversarial Network (CGAN): CGANs represent a novel approach and are a prominent variant of GANs, used for training generative models. The primary function of CGANs is to learn examples from a distribution rather than sampling from the marginal distribution. Sampling in Conditional Generative Adversarial Networks (CGANs) depends on additional auxiliary information, such as labels and data. Figure 6 depicts the paradigm of Conditional Generative Adversarial Networks (CGANs).

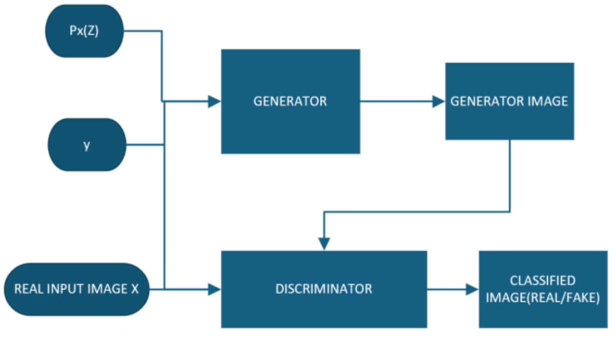

Figure 6. Conditional Generative Adversarial Network Model (Picture credit: Original)

4.2.2 Cycle Generative Adversarial Network (CYCLEGAN)

CycleGAN, proposed by Jun-Yan Zhu et al. in 2017, is a notable variant of generative adversarial networks. This model primarily aims to map images without paired data by employing mapping functions and adversarial loss functions [19].

This technique is mostly employed for picture synthesis of unpaired datasets across diverse domains. Secondly, using this method can reduce training time and memory consumption. It also helps to convert supervised methods into unsupervised ones.

4.2.3 Semantic Guided Generative Adversarial Network

This model employs semantic information as an auxiliary supervisory signal within the UIE network to direct the enhancement process towards semantically pertinent areas while concurrently addressing the problem of blurring image edges.

Additionally, when image degradation and semantic-related features occur simultaneously, semantic information provides prior knowledge to the network, enhancing the model's performance and generalization ability [20]. For instance, the SGAF-GAN proposed by Liu et al. in 2025 is a semantic-guided generative adversarial network, achieving a PSNR of 24.30 and a SSIM of 0.9144 on the SUIM dataset.

This method still has limitations. During color correction, there may be insufficient correction (leaning towards blue or green), or excessive correction (leaning towards red or yellow). Moreover, the output of SGAF-GAN may also present artifacts, as shown in the following Figure 7.

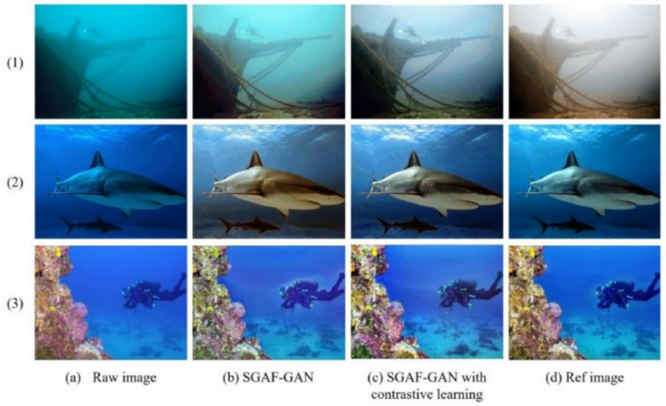

Figure 7. Test results of SGAF-GAN underwater dataset [20]

In image (2)(b), there is a yellowish-green shift; in (1)(b), there is a bluish-green shift; and in (3)(b), there are artifacts. These defects may be caused by introducing inaccurate semantic information into the network.

4.3 Underwater Image Dataset

In the research on image enhancement using generative adversarial networks, various datasets have been adopted for testing and training. These datasets have made significant progress in image enhancement using generative networks. It is precisely because of these datasets that many variants of generative adversarial networks can achieve the expected results [1]. Table 2 lists the datasets used for image enhancement in different research papers [2-11] [16-17].

Table 2. Datasets for Image Enhancement Utilizing Generative Adversarial Networks

Dataset Name	Feature
Enhanced Underwater Vision Perception (EUVP)	It includes 8,670 images of size 256×256, among which 3,700 are used for training [8], aiming to facilitate the supervised training of underwater image enhancement models.
SUIM	The dataset contains 1,635 real underwater images, which are labeled pixel-wise into 8 different types.
RUIE	The RUIE dataset is a large underwater benchmark under natural light, containing over 4,000 images.
SA	This collection is of moderate to small scale, comprising 9,235 photos of sea anemones at a resolution of 256×256, with only a limited number exhibiting good perceptual quality.
T	The T dataset has 9,366 images of marine species

5 Challenges and Future Directions

5.1 The Algorithm Exhibits High Time Complexity.

In the future, while enhancing the performance of the algorithms, emphasis should also be placed on their efficiency. Not only should the effect of image enhancement be satisfactory, but the time complexity of the image enhancement algorithm should also be optimized. The GAN underwater image enhancement algorithm utilizing feature fusion, as discussed by Liu Haoxuan, Lin Shanling, Lin Zhixian, et al., has demonstrated satisfactory results; however, it has also led to an increase in time complexity. In the future, efforts can be made towards higher algorithm execution efficiency [21].

5.2 Insufficiency of Datasets

The quantity and types of underwater image enhancement datasets are inadequate to effectively support the majority of existing deep learning-based methods. Obtaining high-quality datasets is quite challenging. The existing deep learning methods have extremely high requirements for underwater image data, but the available data is relatively scarce. Hence, constructing large-scale and high-quality underwater image enhancement datasets is a significant research orientation in the future.

5.3 Balancing Parameter Quantity and Performance

Some lightweight networks, although highly efficient, have a small number of parameters and thus insufficient enhancement effects. How to ensure that the image enhancement effect reaches or even exceeds the performance of other complex models while maintaining a small model parameter is a major challenge. For example, the enhanced DUnet-GAN is a lightweight network, with its parameter quantity being only 5% of other similar models. Future models need to find a reasonable balance between parameter efficiency and enhancement effect [22].

6 Conclusion

Underwater environments impose limitations that frequently result in color distortion, blurriness, and reduced contrast in captured images or videos. These issues significantly affect the identification of underwater objects and the implementation of advanced underwater operations. Therefore, finding more effective underwater image enhancement techniques is of crucial importance. The swift advancement of computer science has rendered deep learning an effective approach for underwater picture improvement, with generative adversarial networks emerging as a focal point of research. This paper first introduces the principle of underwater imaging and the structure of generative adversarial networks, then discusses the research progress of various underwater image enhancement methods based on GANs, and analyzes the existing datasets. Finally, it lists the challenges faced by this technology and possible future development directions, providing future research directions for researchers in related fields and hoping to be helpful to readers.

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