A Review of Gan-Based Texture Reconstruction of Underwater Images

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Abstract. With the deepening of marine resources development, the importance of underwater image processing technology is becoming more and more prominent. Nevertheless, such images frequently exhibit colour distortion, diminished contrast, and blurred textures due to light scattering and absorption. Although traditional image enhancement methods are effective, they have limitations such as noise amplification and poor environmental adaptability. In recent years, methods based on the Generative Adversarial Network (GAN) have shown significant advantages in texture reconstruction and colour restoration by learning underwater image features through adversarial training. The paper systematically reviews GAN-based texture reconstruction methods for underwater images, comparatively analyze the performance differences of multiple models from early to present and test them on underwater image datasets to quantitatively evaluate their effectiveness based on image quality indicators. The experiments have demonstrated that the method based on Generative Adversarial Network (GAN) outperforms traditional approaches in terms of detail restoration and generalization ability. However, it still has problems such as high computational complexity and data dependence. Future research can combine physical modelling and lightweight design to further enhance real-time processing capabilities and environmental adaptability.

1 Introduction

As demand for marine resource exploration continues to grow, underwater image processing technology has undergone rapid development in recent years. These developments have catalysed the proliferation and innovation of specialized hardware systems, including autonomous underwater vehicles (AUVs), remotely operated vehicles (ROVs), and high-precision dive cameras. Images with severe colour deviation, low contrast, and blurred textures result from the complex optical environment underwater, which is characterized by strong scattering and wavelength-selective absorption of light. This review focuses on the underwater image texture reconstruction methods based on Generative Adversarial Networks (GAN) from the early stage to the present, covering the

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core principles of the algorithms, the design of loss functions, and the comparison of model performances, etc. Besides, this article will also explore the development trends of underwater image enhancement technologies.

Furthermore, this review will introduce traditional methods for texture enhancement of underwater images, which are mainly performed by model-free or physical model-based strategies with limited effectiveness. For example, Histogram Equalization (HE) improves contrast but tends to amplify noise [1], and Dark Channel Prior (DCP) significantly degrades performance in turbid waters due to assumptions that do not match the underwater environment [2].

As deep learning advances quickly, GAN-based techniques provide fresh concepts for reconstructing the texture of underwater images. The underwater image enhancement technology based on Generative Adversarial Networks has been continuously improved from the early WaterGAN proposed by Li et al. which pioneered GAN in the field of underwater image enhancement [3], to the UW-GAN proposed by Wang et al. which adopts a multi-scale dense block structure [4]. The FUnIE-GAN proposed by Islam et al. marks the development of lightweight GAN models [5]. In recent years, techniques based on Generative Adversarial Networks have developed rapidly, such as MuLA-GAN proposed by Bakht et al. which introduces multimodality and attention mechanism [6], and DGD-cGAN proposed by Gonzalez-Sabbagh et al. [7], which achieves a more stable underwater image processing technique by integrating the Generative Adversarial Network (GAN) with physical models.

Quantitative comparisons of model performance were also conducted in this review, where the performance of GAN-based models is analyzed on different datasets based on image quality evaluation metrics for images with a reference image and for images without the aid of a reference image.

2. Underwater Image Degradation Mechanism

The Jaffe-McGlamery model provides a theoretical framework for analyzing underwater optical irradiance by decomposing it into three primary components: direct light, forward-scattered light, and backward-scattered light. The direct light component represents unaltered photons traveling from the target to the imaging sensor. The forward scattering component is the fraction of light that arrives at the imaging system after being scattered by suspended particles in the water while moving, the image becomes blurry. The backward scattering component refers to the part of the light scattered by particles suspended in water from natural or artificial light sources. This scattered light directly enters the imaging system, thereby reducing the image contrast. The Jaffe-McGlamery mathematical model can be expressed as follows:

$$\mathrm{I}(\mathrm{x}) = \mathrm{J}(\mathrm{x}) \cdot \mathrm{t}(\mathrm{x}) + \mathrm{B} \cdot \big(1 - \mathrm{t}(\mathrm{x})\big) \tag{1}$$

where I(x) is the degraded image captured by the sensor, i.e., the observed image; J(x) refers to the ideal non-degraded clear image, i.e., the recovered image of the target; t(x) is a transmittance map describing the proportion of light reaching the camera, correlated with the medium turbidity, and the distance B is the backward-scattered light, caused by the water's suspended particles reflecting ambient light.

3. Classification of Underwater Image Texture Reconstruction Methods

3.1 Conventional underwater image enhancement methods

3.1.1 Model-free methods

Instead of relying on a physical model of underwater imaging, model-free methodologies enhance visual clarity by directly manipulating pixel values without leveraging physical imaging models. Common model-free methods include:
Gray World Algorithm: This method operates under the assumption that the average reflectance across RGB channels in natural scenes is balanced. Colour cast—caused by unequal channel gains during imaging—is corrected by modulating RGB gains to normalize the image's average colour toward a neutral gray [8]. However, the grayscale world algorithm assumes that the image colour distribution is uniform, and the correction effect is limited when the colour deviation of the underwater image is severe or unevenly distributed [9].

Histogram Equalization (HE): By redistributing the pixel values of an image, the dynamic range of the gray scale of the image is extended, thus enhancing the contrast of the image. However, the HE algorithm is prone to over-enhancement of noise, especially for the existing noise in the underwater image will be further amplified, resulting in image quality degradation, and is not suitable for direct application in underwater image enhancement [1].

Contrast Limited Adaptive Histogram Equalization (CLAHE): The CLAHE algorithm is an improved version of HE, which divides the image into small regions (tiles), performs histogram equalization within each region, and limits the degree of contrast enhancement, thus reducing the noise amplification effect [10]. thereby reducing the noise amplification effect [10]. CLAHE improves the drawbacks of HE to a certain extent, but its colour restoration capability is still limited and is not effective for underwater images with severe colour deviation [11].

3.1.2 Physical model-based approach

Physical model-based approaches aim to simulate image degradation by modelling the physical processes of underwater imaging and conduct image restoration through parameter estimation of the established model. Representative methods include:

Dark Channel Prior (DCP): Derived from terrestrial haze removal, DCP exploits the statistical observation that non-sky regions exhibit minimal pixel values in at least one RGB channel. By estimating dark channels, it inverts transmittance and background light to reconstruct images [2]. However, discrepancies between underwater and atmospheric optical properties—particularly under variable depth or turbidity—severely constrain DCP's applicability [12].

Maximum Attenuation Identification (MAI): Based on wavelength-dependent light attenuation in water, the MAI algorithm calculates the maximum degree of attenuation for different colour channels to restore the image [13].The performance of the MAI algorithm relies on accurate assumptions about the type of the water body, and the ability to generalize is weak when there is a complex water body composition or changes in ambient light [14].

3.2 Generative Adversarial Network-based Texture Reconstruction Method for Underwater Images

Underwater images commonly exhibit lower contrast, colour shift and blurring as a result of light absorption and scattering, which have a serious impact on the application of computer vision systems to underwater environments. Methods of GAN have excellent performance in the field of image enhancement and become a popular direction for texture reconstruction and enhancement of underwater images. This paragraph will comb through the early to present GAN-based underwater image enhancement methods and summarize and analyze the core ideas and technical features of the methods.

3.2.1 Water-GAN

Li et al. proposed Water-GAN in 2017 [3], which acquires a realistic representation of the water column characteristics at a specific underwater location through the use of real unlabelled images, while achieving the dual functions of underwater image generation and colour correction under unsupervised conditions by combining physical modelling and deep learning. The core principle of Water-GAN is to generate a network by inputting an airborne or land-based RGB-D image The core principle of Water-GAN is to generate a network by inputting airborne or land-based RGB-D images and a set of underwater image samples in an adversarial manner, and train a colour correction network based on the data generated by Water-GAN to restore the true colour of underwater images, where the colour correction network adopts a two-step architecture of relative depth estimation and colour restoration. The loss function of Water-GAN realizes high-quality underwater image generation and enhancement through adversarial training, physical constraints, and content consistency under multiple supervision. image generation and enhancement.

The advantage of Water-GAN is that it does not require pairs of data making it less dependent on data, while using end-to-end learning to effectively avoid complex post-processing. However, the model suffers from high computational cost and insufficient generalization ability, which makes it difficult to meet the current demand for real-time and lightweight.

3.2.2 UW-GAN

Wang et al. in 2019 proposed UW-GAN for colour restoration and defogging of underwater images in response to the problems of colour distortion, fogging, and low contrast in underwater images [4], to address the deficiencies of existing methods in colour correction and defogging effects. The core idea of UW-GAN is to take aerial RGB-D images and site-specific underwater image samples as the unsupervised GAN architecture as inputs to counter-train the generative network. Secondly, a synthetic underwater image dataset is used to train a U-Net based recovery network for colour recovery and defogging. The technique of UW-GAN is characterized by unsupervised learning conditions for generating images, and the use of a multi-scale dense block structure in order to improve the feature extraction capability of the augmented model. Where different loss functions have different effects on U-Net [15], Wang et al. used the following loss functions [4]:
L1 loss:

$$\mathcal{L}^{l1}(X)=\frac{1}{N}\sum_{x\in X}|g(x)-r(x)| \quad (2)$$

L2 loss:

$$\mathcal{L}^{l2}(X)=\frac{1}{N}\sum_{x\in X}\big(g(x)-r(x)\big)^2 \tag{3}$$

In the mathematical formula x is the index of the pixel in region X, g(x) is the pixel value of the U-Net reconstructed image in region X, and r(x) is the pixel value corresponding to the true value.

The advantage of UW-GAN is that it does not require pairs of data, which makes the annotation cost lower, and at the same time, it is effective in correcting colour distortion, and its model effectiveness and robustness are excellent. However, the model is limited in its ability to repair detailed textures.

3.2.3 FUnIE-GAN

In 2020 Islam et al. proposed FUnIE-GAN [5] for the real-time problem of underwater image enhancement, which uses a lightweight U-Net generator and a Patch-GAN discriminator [16]. The model is characterized by the architecture of a supervised GAN, which allows the encoder to extract features and the decoder to reconstruct the image based on the U-Net structure. The ability of the model to recover details is improved by using jump connections to preserve low-level features. The small discriminator in PatchGAN, only determines whether the local patches of the image are true or not, while going more on local image quality rather than global consistency. Islam et al. trained the model using the EUVP dataset [5] with the following loss function:

Condition adversarial loss：

$$\mathcal{L}_{cGAN}(G,D)=\mathbb{E}_{X,Y}[logD(Y)]+\mathbb{E}_{X,Y}[log\big(1-D(X,G(X,Z))\big)] \tag{4}$$

A mapping G ({X, Z}→ Y) is learned by a standard conditional GAN-based model. Where X(Y) is representative of the source domain. Z is used to denote random noise [17].

L1 loss:

$$\mathcal{L}_1(G)=\mathbb{E}_{X,Y,Z}[\|\mathrm{Y}-\mathrm{G}(X,Z)\|_1] \tag{5}$$

Incorporating L1 (L2) loss into the objective function can help G learn to sample in a globally similar space in an L1 (L2) manner, as indicated by the existing methods [5][16][18].

Content loss:

$$\mathcal{L}_{con}(G)=\mathbb{E}_{X,Y,Z}[\|\Phi(Y)-\Phi(G(X,Z))\|_2] \tag{6}$$

FUnIE-GAN has strong generalization ability, excellent contrast and colour correction, and is suitable for embedded development due to its small number of network channels, lightweight convolutional kernel, and lightweight model. However, it has limited performance on high-noise scenes as well as poor results on extremely degraded images.

3.2.4 MuLA-GAN

MuLA-GAN for underwater image restoration was proposed by Bakht, A. B. et al.[6] The core idea of the model is to draw attention of the network to the colour-biased and structurally distorted regions of an underwater image by constructing an end-to-end generative adversarial network that integrates the spatial attention [19] and channel attention [20] modules where the model can be optimized for multiple tasks (e.g., colour correction, defogging.) at the same time by using a multitasking approach to learning, detail enhancement), thus improving the generalization ability of the model.

The loss function of MuLA-GAN incorporates adversarial loss, MAE loss (L1 loss), and perceptual loss which based on the VGG-19 network [21]. Its loss function is as follows:

Adversarial Loss:

$$\mathcal{L}_{adv}(G, D) = \mathbb{E}_{X,Y}[logD(X,\ Y)] + \mathbb{E}_{X,Z}\left[log\left(1 - D\big(X, G(X,Z)\big)\right)\right] \tag{7}$$

Perceptual Loss:

$$\mathcal{L}_{per} = \frac{1}{C_j H_j W_j}\sum_j \left\|\Phi_j(Y) - \Phi_j\big(G(X,Z)\big)\right\| \tag{8}$$

where j refers to the selected layer of the VGG-19 network, and Cj, Hj, and Wj refer to the number of channels, height, and width, respectively, of the j^{th} layer of the VGG network [6][22].

MAE Loss:

$$\mathcal{L}_1(G) = \mathbb{E}_{X,Y,Z}[\|\mathrm{Y} - \mathrm{G}(X,Z)\|_1] \tag{9}$$

The multi-layer attention mechanism adopted by MuLA-GAN can better restore the underwater image texture and enrich the image details, and by introducing the spatial channel attention [6], the model performance is excellent in multiple datasets. However, MuLA-GAN does not perform as well as FUnIE-GAN [5] in scenes such as green distortion. As well as depending on the size of the input image, resulting in different computational complexity, the level of restoration real-time needs to be improved.

3.2.5 DGD-cGAN

Salma Gonzalez-Sabbagh et al. proposed DGD-cGAN [7], which employs a conditional GAN (cGAN) architecture to enhance underwater defogging effect by incorporating physical models. The technical approach of DGD-cGAN is to design two generators and one discriminator. In the two-generator architecture, the first generator uses the underwater image as input and the predicted underwater scene as output. The second generator uses a loss function based on UIFM [23] (as a consistency constraint) [7] to learn how to estimate underwater transmission and glare. Thus, the dual-generator architecture can solve the problem of fading and astigmatism in underwater images.

The advantages of DGD-cGAN are that its model is more stable, converges faster, and outperforms ordinary GANs. the shortcomings are the high dependence on underwater images, the need for supervised learning of pairs of underwater-clear images, and the low real-time performance due to the high computational complexity.

4. Comparative Analysis of Model Performance

In this paragraph, the performance of Generative Adversarial Networks (GANs) in the tasks of underwater image enhancement from early times to the present day is systematically compared with the datasets the paper used, which are UIEB [24], EUVP [5] and U45 [25]. To comprehensively evaluate the model's performance in image quality enhancement, this paper selected two image quality evaluation metrics: Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM), using the reference image as a benchmark [26]. PSNR and SSIM are employed to measure the similarity between the enhanced image and the reference image. Higher values of PSNR and SSIM indicate greater structural and texture similarity. For the no-reference image quality evaluation metrics, including UIQM [27], UCIQE [28], and NIQE [29], UIQM and UCIQE are primarily utilized to assess the visual quality of images in underwater environments, while NIQE is employed to quantify the naturalness and realism of images. Higher scores in UIQM and UCIQE suggest better alignment with human visual perception, whereas lower NIQE scores indicate superior visual quality. By testing on two datasets with different distributions, the paper can be able to more comprehensively compare the generalization ability and stability of each GAN model in different scenarios.

Shown in Table 1 are the quantitative data from the UIEB test dataset with reference images using PSNR and SSIM.

Table 1 Quantitative comparison of referenced images using PSNR and SSIM on the UIEB test dataset

Method	FUnIE-GAN [6]	MuLA-GAN [6]	DGD-cGAN [7]	UGAN [7]	Fusion [6]	U-Transformer [6]
PSNR	21.03	<u>25.59</u>	23.59	18.08	20.87	21.64
SSIM	0.775	<u>0.893</u>	0.707	0.621	0.857	0.778

Shown in Table 2 is the quantitative data for the EUVP test dataset with reference images using PSNR and SSIM.

Table 2 Quantitatively comparing referenced images using PSNR and SSIM on the EUVP test dataset

Method	FUnIE-GAN [30]	CycleGAN [30]	Pix2Pix [30]	UGAN-P [30]	Res-WGAN [30]	LS-GAN [30]
PSNR	<u>21.92</u>	17.14	20.27	19.59	16.46	17.83
SSIM	<u>0.8876</u>	0.6401	0.7081	0.6685	0.5762	0.6725

Table 3 displays quantitative data and reference images using UIQM, UCIQE, and NIQE for the EUVP test dataset.

Table 3: Quantitative comparison of referenced images using UIQM, UCIQE, NIQE on U45 test dataset

Method	FUnIE-GAN [6]	MuLA-GAN [6]	U-Transformer [6]	Water-Net [6]	Fusion [6]
UIQM	3.21	<u>3.23</u>	3.10	3.18	3.14
UCIQE	0.602	<u>0.612</u>	0.553	0.587	0.532
NIQE	3.95	<u>3.86</u>	4.30	3.91	3.97

5. Existing Challenges

5.1 Data dependency issues

Most GAN architectures (e.g., Pix2Pix [31], UGAN [32], UWGAN [4]) require a substantial collection of paired clear or degraded images for training. However, getting high-quality underwater paired images in the real world is challenging, due to issues such as underwater visibility limitations, high equipment costs, and the inability to replicate the scene.

For example, Pix2Pix and UGAN have superior results under the condition of good image alignment, but the performance drops sharply when lacking paired data; WaterGAN constructs a physical model to simulate the degradation process of underwater images, which is then used for unsupervised training. However, the synthetic images generated by this method still fail to accurately match real scenes; subsequent methods such as UW-CycleGAN [33], Sea-thru (CVPR 2020) [34] and other methods further try to solve the unsupervised training problem with cross-domain mapping and image reconstruction. However, there still exists a huge discrepancy, i.e., the synthesized data cannot fully cover the variations in complex real conditions, leading to unstable model results on real underwater images.

5.2 Adaptability to complex environments

Underwater environments are variable and complex, such as water turbidity, light attenuation, colour distortion, and scattered light interference. Most GAN models perform well in ideal environments but show poor robustness in extreme degradation scenarios. For example, FUnIE-GAN is able to improve image visibility in shallow water clear environments, but the colour correction is inaccurate in ports or deep-sea complex backgrounds; CycleGAN is capable of domain migration [35], but is unable to maintain structural details, and is prone to artifacts in extreme scattering environments.

5.3 Real-time requirements

Most of the current GAN-based models have high computational complexity and slow inference speed, which are not suitable for deployment on edge computing devices, limiting their application in scenarios such as AUVs, ROVs, and dive cameras. For example, although the multi-level attention network structure used by MuLA-GAN can improve the visual quality, the inference speed is slower according to the larger size of the input image; CycleGAN, although lighter, still requires multiple convolution + deconvolution on certain structures, and the deployment of it on Jetson Nano [36] will result in frame dropping; the introduction of the temporal consistency module in T-UIGAN [37] that increases the computational complexity.

5.4 Multitasking trade-offs

Texture reconstruction of underwater images involves multiple objectives, such as colour correction, contrast enhancement, defogging, denoising, and structure recovery. However, these objectives often conflict with each other, and it is difficult to balance between the loss functions in training. For example, UGAN can balance colour loss and content loss, but there is a contradiction between colour fidelity and texture details; Rest-GAN favours structure preservation [38], which can lead to a lack of uniformity in image colour style. At the same time, too many loss functions are introduced instead, which can lead to poor training convergence, and the problem of GAN's own susceptibility to oscillation is amplified.

6. Future Research Directions

6.1 Incorporate physical modelling to enhance realism

Traditional GANs rely only on data-driven methods to learn features, while the degradation of underwater images has complex physical laws (e.g., light scattering, absorption, etc.), and the combination of physical models can improve the realism and stability of GAN-generated images.

6.2. lightweight and efficient GAN models supporting real-time processing

Existing GAN models have large computational costs and are not suitable for embedded devices or real-time processing requirements. Today's emerging techniques such as pruning, knowledge distillation, and quantization can greatly reduce the computational cost to develop computationally efficient and low-power adversarial generative networks for underwater image processing to support real-time applications (e.g., underwater robots, underwater cameras, AR/VR).

6.3. multimodal fusion for improved underwater image understanding

Currently, relying on RGB images for enhancement cannot solve the problem of complex underwater environments (e.g., low-light or high turbidity scenes). Combining multimodal data such as RGB, depth, and sonar can provide richer features for the model and improve the adaptability of GAN to complex underwater environments.

7. Conclusion

Over the past few years, GAN-based underwater image texture reconstruction methods have made significant progress, from the early WaterGAN, CycleGAN to the subsequent such as FUnIE-GAN, MuLA-GAN, DGD-cGAN, etc., and the different methods are constantly upgraded in the aspects of colour restoration, contrast enhancement, de-fogging and de-noising, etc. This paper systematically analyzes and compares the mainstream GAN methods in the aspects of technical principle, loss design, supervision, etc., and summarizes the current development status of GAN processing in the future research. This paper systematically analyzes and compares the mainstream GAN methods in terms of technical principle, loss design, supervision mode, etc., summarizes the current development status of GAN processing of underwater images, and at the same time, puts forward the expectations for the future research, such as combining the physical model, improving the model lightweight, reducing the computational cost, and multimodal fusion. The paper believe that future underwater image enhancement will achieve greater breakthroughs in visual quality, physical applications and intelligence level.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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