Deep Learning in Underwater Image Enhancement: Models and Marine Impact

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Abstract: Underwater images are of great significance in marine related fields, but the complex underwater environment causes problems such as color distortion and low contrast, which seriously affect information extraction. This study focuses on underwater image enhancement methods based on deep learning, and conducts in-depth analysis and comparative experiments on various models such as FusionEnhance and CycleGAN. Train the model using the EUVP dataset and test it using the UFO-120 dataset, and evaluate its performance using PSNR, SSIM, and UIQMS metrics. The experimental results show that UWCNN performs the best in PSNR and SSIM metrics, with outstanding abilities in denoising and preserving image structure; UGAN performs excellently in the UIQMS metric, with a significant overall improvement in image quality. The study also found that different models have their own advantages and disadvantages in quantitative and qualitative analysis, such as WF Diff, which has excellent quantitative indicators but less detail retention than Pix2pix. This study provides important references for the development of underwater image enhancement technology, while pointing out the limitations of current research in model selection, dataset representativeness, and evaluation indicators.

Keywords—underwater image enhancement, deep learning, WF-Diff, PSNR, UIQMS

I. INTRODUCTION

Underwater images have extraordinary significance in marine science, engineering, and military applications, and are an important way to obtain ocean information. However, the complex underwater environment leads to color distortion, low contrast, and blurry details in images, which seriously restricts the effective utilization of image information [1]. Therefore, underwater image enhancement technology has attracted much attention.

At present, underwater image enhancement methods are mainly divided into physical model-based and deep learning methods. The former relies on mathematical modeling to restore images, but due to the complex and difficult to measure parameters in underwater environments, its application is limited [2]. Deep learning methods rely on data learning to achieve image enhancement, and with their widespread application in the field of computer vision, they have opened up new paths for underwater image enhancement.

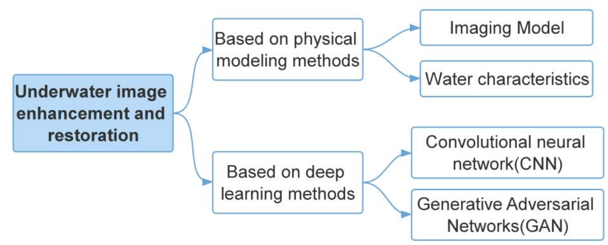

Fig. 1. Classification map of underwater image enhancement methods

This article focuses on deep learning underwater image enhancement methods, analyzes various model principles, and conducts comparative experiments. Using the EUVP dataset [3] for training and the UFO-120 dataset [4] for testing, performance was evaluated using indicators such as SSIM [5], PSNR [6], and UIQMS [7], with the aim of providing reference for the development and related applications of this technology.

II. UNDERWATER IMAGE ENHANCEMENT METHODS

A. Physics based methods

Underwater imaging is mainly based on the Jaffe McGlamery model [8], which indicates that underwater images are composed of three light components: direct scattering, forward scattering, and backward scattering. Directly scattered light comes from the light directly entering the camera from the subject being photographed; Forward scattered light is reflected or radiated from the target surface and enters the imaging system after being scattered by suspended particles in water, resulting in blurred images; Backscattered light is natural light that enters the imaging system after being scattered by suspended particles, resulting in low contrast in the image [9]. The formula is as follows:

$$I(x) = J(x)t(x) + B_{\lambda}(1 - t(x)),\ \lambda \in \{r, g, b\}$$

Where, $I(x)$ is the degraded image, $J(x)$ is the potential scene irradiance, B_λ is the global light, λ represents different color channels, $t(x)$ represents the medium transmittance, i represents the proportion of light that has not reached the camera, which is defined as: $t(x) = e^{-\beta_\lambda d(x)}$, where β_λ is the medium reflection coefficient, which is related to the degree of color attenuation in the transmission medium, and β_λ represents the distance between the camera and the object in the image.

B. *Methods based on deep learning*

With the rapid development of deep learning, underwater image enhancement methods based on deep neural networks have gradually become an effective way to solve the problem of underwater image degradation. Compared to traditional image processing methods, deep learning can automatically learn hidden patterns in underwater images, not only improving image quality but also adapting to different underwater environments. In recent years, deep learning methods have mainly been divided into convolutional neural network (CNN) [11] based methods and generative adversarial network (GANs) [12] based methods.

Some studies have designed network structures specifically for underwater image enhancement based on convolutional neural networks (CNN). For example, UWCNN (Underwater Convolutional Neural Network) effectively improves the color, contrast, and detail restoration of underwater images by combining their physical characteristics, such as transmission maps and background light estimation. UWCNN adopts a two-stage network structure, first separating and processing low-frequency and high-frequency information, then enhancing each part, and finally synthesizing the restored image [13]. In addition, Water-Net adopts a deep convolutional network, which is an end-to-end underwater image enhancement network that focuses on dehazing and detail restoration of underwater images, demonstrating good robustness in complex underwater environments.

Models based on Generative Adversarial Networks (GANs) have also been widely used in underwater image enhancement. CycleGAN [14] and pix2pix [15], as representative methods of image to image conversion, can successfully enhance underwater images through training without paired data. In addition, Funie_GAN [16] achieves real-time image enhancement through Conditional Generative Adversarial Networks (cGAN), significantly improving the visual quality of underwater images, especially suitable for dynamic underwater scenes. In addition, Water_CycleGAN [17] , as a variant of CycleGAN, is specifically optimized for dehazing and enhancing underwater images, effectively addressing optical distortion issues in underwater images and restoring image clarity.

Overall, deep-learning-based underwater image enhancement methods, by automatically learning features and environment characteristics, have achieved significant results. However, current methods face issues like limited dataset diversity and low computational efficiency. Improving their generalization and real - time performance remains a key future research focus.

III. UNDERWATER IMAGE ENHANCEMENT AND RESTORATION METHOD BASED ON DEEP LEARNING

A. *Method based on CNN*

Most CNN-based underwater image enhancement models employ a U-Net [20] like architecture, consisting of an encoder and a decoder, with skip connections to preserve low-level image features and spatial details. The encoder utilizes convolutional and pooling layers for downsampling to extract features, while the decoder applies deconvolutional and upsampling layers to reconstruct and generate enhanced images.

In feature extraction, CNNs can autonomously learn representations of underwater image attributes such as edges, textures, and colors. By stacking multiple convolutional layers, these networks extract features at varying levels of abstraction, enabling a deeper understanding of image content. Feature fusion techniques are also widely adopted, integrating characteristics from different layers to leverage multi-scale information, thereby enhancing the overall effectiveness of the enhancement process.

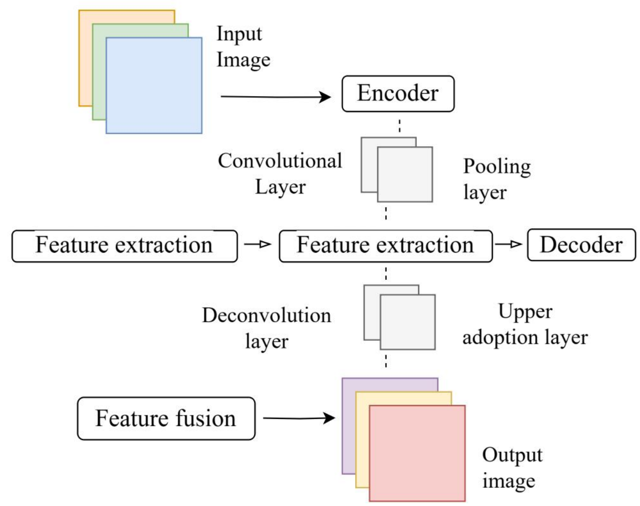

Fig. 2. The workflow of the CNN-based method

Models for underwater image enhancement relying on convolutional neural networks (CNNs) [21] generally demand a large volume of annotated data to train effectively, aiming to discern the characteristics and enhancement rules of underwater visuals. Yet, securing high-quality labeled datasets remains difficult due to the intricate and ever-changing underwater conditions. To tackle this issue, certain studies leverage data augmentation strategies, including techniques like rotation, mirroring, and trimming, to enrich the variety of the training dataset.

Certain CNN-based approaches enable effective color correction and enhancement by capturing the color characteristics and distributional properties of underwater images. For instance, the UIE-Net [22] framework, developed by Wang and colleagues, jointly addresses color correction and haze removal, mitigating color distortions in underwater scenes while enhancing the vibrancy of colors.

CNN-based models can also be applied to underwater image restoration and super-resolution reconstruction. For instance, the algorithm proposed by integrates methods such as the Retinex algorithm [23] , gamma correction, and dark channel [24] prior to achieve high-resolution reconstruction of underwater images.

B. *GAN based approach*

The GAN-based underwater image enhancement model generates realistic underwater images through adversarial Jéraining between the generator and the discriminator. During the training process, the generator attempts to produce images similar to real underwater images, while the discriminator strives to distinguish between the generated images and real ones. Through this adversarial training, the generator can continuously learn and optimize, producing increasingly realistic underwater images.

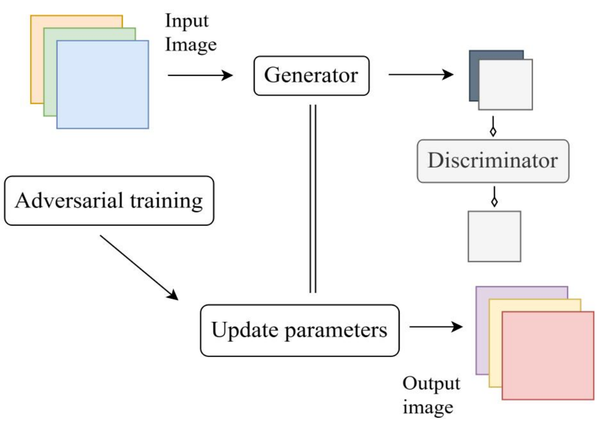

Fig. 3. The workflow of GAN-based methods

The advantage of GANs lies in their ability to generate diverse and creative images, making them suitable for handling complex underwater image enhancement tasks. However, GANs also face certain challenges, such as training instability and mode collapse. To address these issues, some studies have improved the loss functions and training algorithms of GANs, such as adopting Wasserstein GAN and enhancing the discriminator structure.

CycleGAN [25] is an unsupervised GAN model that is able to transform images from one domain to another while preserving the structural information of the image. In underwater image enhancement, CycleGAN can convert blurred and distorted underwater images into clear and realistic images. In addition, some variant models based on CycleGAN, such as Adaptive Weighted [26] Multi-Discriminator CycleGAN, have also been applied to the field of underwater image enhancement, and the enhancement effect of underwater images has been improved by improving the model structure and training algorithm.

cGAN [27] is a model that adds conditional information to the original GAN, which can be class labels, image attributes, etc. In underwater image enhancement, cGAN can generate underwater images with specific properties based on the conditions of the input, for example, generate corresponding color-corrected images based on the type of underwater scene.

IV. EXPERIMENTAL RESULTS AND COMPARATIVE ANALYSIS

A. *Experimental setup*

To accurately compare the performance of various deep learning models in underwater image enhancement, we designed a rigorous experimental setup. The training set was selected from the EUVP dataset, which encompasses a diverse range of underwater image scenes (including different depths, water qualities, and lighting conditions), providing ample samples for model training. The test set was chosen from the UFO-120 dataset, whose images are representative and independent of the training set, effectively evaluating the generalization ability of the models.

The research focuses on several deep learning models, including FusionEnhance [29], CycleGAN [30], Pix2Pix [31], UWCNN [32], UGAN [33], FUnIE-GAN [34], Water_CycleGAN [35], WF-Diff [36], and Water_Net [37]. During training, hyperparameter tuning was conducted for each model to ensure optimal performance. All experiments were conducted on a server equipped with Python 3.8.2, PyTorch 2.4.1, and an NVIDIA GRID V100D-32Q GPU.

B. *Evaluation indicators*

To comprehensively evaluate the performance of different models in underwater image enhancement, this paper employs three commonly used image quality assessment metrics. The SSIM (Structural Similarity Index) [38] is utilized to measure the similarity between the enhanced image and the reference image, taking into account luminance, contrast, and structural information. It is one of the important metrics for assessing image quality. The calculation formula for SSIM is as follows:

$$\mathrm{SSIM}(x,y)=\frac{(2\mu_x\mu_y+C_1)(2\sigma_{xy}+C_2)}{(\mu_x^2+\mu_y^2+C_1)(\sigma_x^2+\sigma_y^2+C_2)}$$

Where,x and y represent the enhanced image and the reference image, respectively. e and f are the means of x and y , while μ_x and μ_y are the variances of x and y . σ_{xy} denotes the covariance between x and y . C_1 and C_2 are constants used to stabilize the division operation.

PSNR (Peak signal-to-Noise Ratio) [39] is another important index to measure the image quality, which can evaluate the distortion degree of the image. The PSNR is calculated as：

$$\mathrm{PSNR}=10\log_{10}(255^2/\mathrm{MSE}(x,y))$$

Where, MSE (Mean Squared Error) refers to the average of the squared differences between the pixel values of the enhanced image and those of the reference image.

UIQMS [40] is a comprehensive image quality assessment metric that combines the perceptual quality and visual effect of an image to comprehensively measure the quality of an enhanced image.These indicators can evaluate the enhancement effect of the model from multiple dimensions to ensure the comprehensiveness and accuracy of the evaluation results.

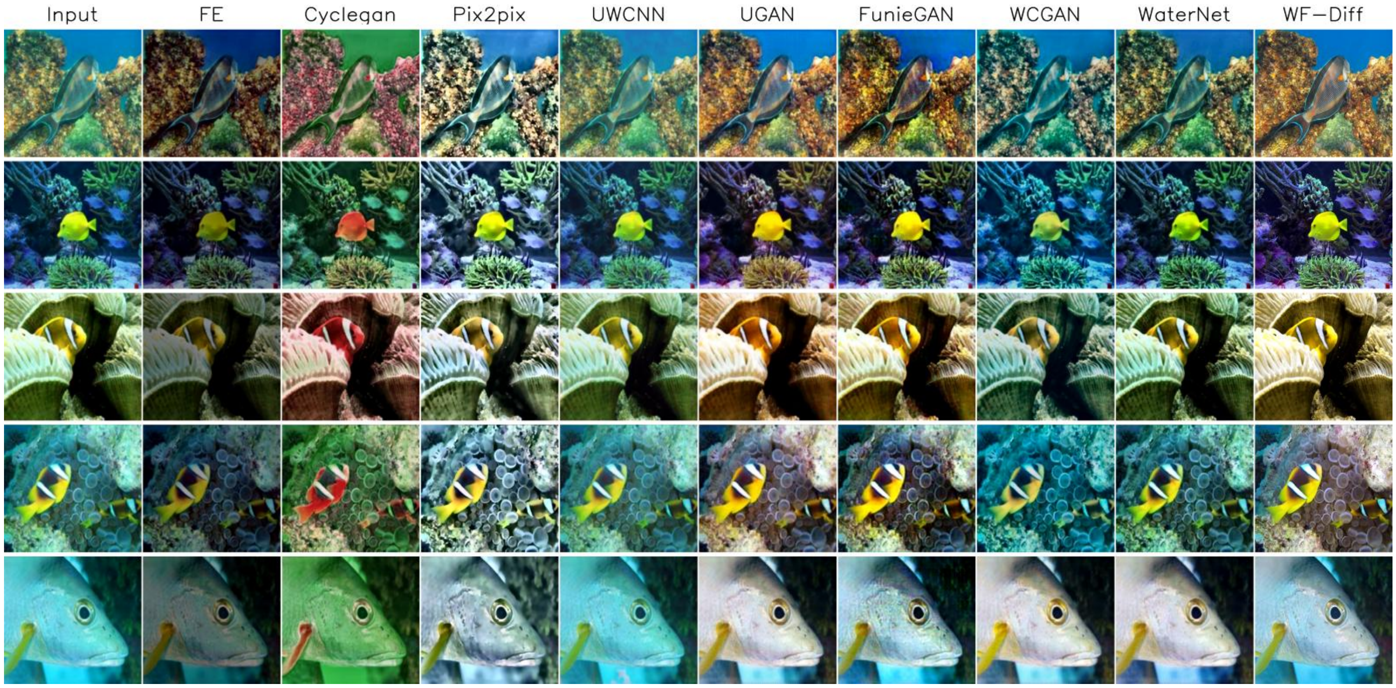

Fig. 4. Qualitative comparison chart of different images

C. Comparative

TABLE I. EVALUATION INDICATOR RESULTS TABLE

Method	PSNR	SSIM	UIQMS
FE	15.44±3.77	0.80±0.060	2.15±0.474
CycleGAN	23.37±2.83	0.79±0.639	2.97±0.351
Pix2pix	16.90±1.56	0.69±0.047	2.26±0.317
UWCNN	24.78±4.07	0.89±0.060	2.89±0.365
UGAN	21.99±2.64	0.82±0.043	3.01±0.353
FUnIE_GAN	22.13±2.14	0.69±0.510	2.56±0.427
WCGAN	21.73±2.94	0.76±0.548	1.88±0.448
Water_Net	24.02±2.08	0.88±0.381	2.76±0.371
WF-Diff	27.18±1.98	0.92±0.091	3.21±0.352

In terms of PSNR index, the higher the value of PSNR, the better the effect of image denoising and definition improvement. In the experiment, WF-Diff [41] and UWCNN perform well, with PSNR values of 27.18 and 24.78, respectively, and the effect of denoising and sharpness enhancement is significant. However, FE and Pix2pix perform poorly, with PSNR only 15.44 and large standard deviation, and poor performance stability.

The SSIM index reflects the similarity of image brightness, contrast and structural information, and the closer to 1 indicates the better structure preservation. WF-Diff leads with 0.92, showing strong and stable structure retention. The SSIM value of Pix2pix and Funie_GAN [42] is only 0.69, and the standard deviation of Funie_GAN is 0.510, which maintains poor stability of the structure on different images.

UIQMS is used to comprehensively evaluate image perception and visual effects. UGAN has the best performance with a score of 3.01, and the comprehensive image quality improvement effect is good and stable. Water_CycleGAN [43] performs poorly, with a UIQMS value of only 1.88, and the overall quality improvement is not good and fluctuates greatly.

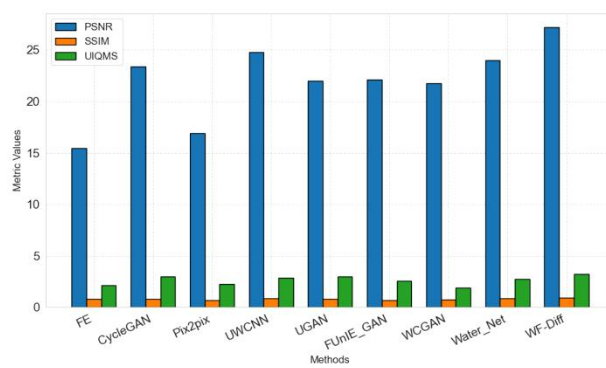

Fig. 5. Performance Comparison of Underwater Image Enhancement Methods

In terms of quantitative indicators, WF Diff performs well in PSNR and SSIM, but in qualitative analysis, Pix2pix performs better in preserving image details; UGAN leads the UIQMS index, and in qualitative analysis, its enhanced image quality is good, with a significant overall improvement effect; Pix2pix has good qualitative analysis performance and excellent detail preservation, which contrasts with its poor performance in PSNR and SSIM; Water_CycleGAN performs well in color reproduction during qualitative analysis, which is in line with human visual effects, but the UIQMS index is not satisfactory; The visual effect of CycleGAN shows a significant difference in color reproduction compared to the original image, but its scores in PSNR, SSIM, and UIQMS indicators are still acceptable; The UGAN restored image appears brighter, and its enhancement effect on underwater dark features is better than other models.

CONCLUSION

This study delves into the enhancement techniques for underwater images, comparing methods based on physical models and deep learning, and further investigating various deep learning models. Physical-based methods face limitations due to the complex underwater environment, where parameters are difficult to obtain and adaptability is poor. As a result, deep learning methods have become the mainstream approach. Different models exhibit their own strengths and weaknesses in terms of evaluation metrics. For instance, UWCNN achieves the best performance in PSNR and SSIM metrics, while UGAN stands out in the UIQMS metric. Moreover, each model demonstrates distinct characteristics in both quantitative metrics and qualitative analysis. Despite the achievements made, there are still limitations in model selection and the representativeness of datasets, and the evaluation metrics fail to fully reflect human visual perception. Future research can be further explored in aspects such as model innovation, dataset expansion, and improvement of evaluation metrics, and the technology can be applied to practical scenarios to promote further development.

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