Mathematical Modeling and Algorithm Application
ISSN: 3006-0842 | Vol. 5, No. 3, 2025

Deep Learning-Based Joint Enhancement for Compound-Degraded Underwater Imagery

Yue Wu*, Tingyu Huang, Yiwei Ma, Shichang Sun

College of Computer Science and Engineering, Dalian Minzu University, Dalian, China
* **Corresponding author**: Yue Wu (Email: 13125477066@163.com)

Abstract: In complex and dynamic underwater environments, different scenarios are often intertwined with multiple image degradation factors, such as color shift, low illumination, and blur. These composite degradation characteristics make enhancement methods tailored to single scenarios struggle to meet comprehensive requirements. This study aims to design a multi-functional underwater image enhancement model capable of adapting to the challenges of various complex scenarios. The model takes into account diverse degradation features and utilizes image data for validation and optimization. The final enhancement effect is evaluated through both visual display of images and quantitative metrics (including PSNR, UCIQE and UIQM).

Keywords: Deep Learning; Image Enhancement; Data Processing.

1. Introduction

Underwater image enhancement has become a critical area of research due to the growing demand for high-quality underwater images in applications such as deep-sea exploration, marine biodiversity studies, and seabed resource investigations. However, underwater environments inherently degrade image quality due to light absorption, scattering, and the presence of suspended particles, resulting in blurriness, color distortions, and reduced contrast[2]. These issues severely affect the visual clarity required for analysis and interpretation.

Despite advancements in traditional and deep learning-based approaches, the diversity of underwater conditions, such as varying turbidity, depth, and lighting, poses challenges for achieving generalized solutions[1]. Many existing methods struggle to balance color distortions and restore fine details accurately in complex real-world scenarios.

To address these challenges, this study focuses on the statistical analysis ofunderwater image degradation, the construction of degradation models, and the development of scenario-specific enhancement methods. Performance metrics such as PSNR, UCIQE, and UIQM are employed to evaluate the quality improvements achieved through these methods.

In complex underwater environments, image degradation factors such as color cast, low light, and blurriness often coexist, resulting in compounded degradation that cannot be effectively addressed by single-scenario enhancement methods. This study aims to develop a multifunctional underwater image enhancement model capable of handling diverse degradation patterns. By integrating degradation features and employing advanced technologies such as deep learning, the model adapts to various underwater scenarios and provides robust solutions for enhancing image quality.

The proposed model will be validated using the provided image dataset, with results assessed through visual comparisons and quantitative metrics, including PSNR, UCIQE and UIQM.

In real-world applications, underwater image degradation often varies significantly due to environmental differences. While specific enhancement techniques may per-form well for addressing a particular issue, such as color cast, low light, or blurriness, their applicability is usually limited to specific conditions. In contrast, comprehen-sive enhancement techniques are better suited to handle multiple types of degradation simultaneously, making them more appropriate for complex underwater environments.

This study investigates the effectiveness of single versus comprehensive enhance-ment techniques in diverse underwater scenarios through experimental comparisons, offering practical recommendations for real-world applications. For underwater scenes with singular degradation characteristics, targeted techniques can be employed to opti-mize efficiency. However, for more complex scenarios involving compounded degra-dation, comprehensive enhancement methods are recommended to achieve balanced improvements in color, brightness, and clarity.

2. Model

To address the challenges of underwater image enhancement in complex scenarios, we propose a deep learning-based multi-module joint enhancement model. This model is designed to enhance and restore underwater images in challenging environments through the following modules.

2.1. Label Module

This module preprocesses the input images and includes the following functional-ities:

•Correct color bias: Adjusts the image colors to compensate for the impact of underwater environments on light, ensuring color fidelity.

•Increase brightness: Enhances the brightness of the images, improving visibility and making them clearer.

•Enhance sharpness: Improves image sharpness to highlight fine details and tex-tures more effectively.

2.2. Data Augmentation

Aiming at the specific issues of underwater images, we have designed specific augmentation methods to perform data augmentation on the input images, thereby improving the generalization ability of the model.

• Color Correction: Histogram equalization is applied to each color channel (RGB) to address the color shift problem.

•Brightness Enhancement: Improving the image brightness by increasing the brightness value.

• Deblurring Processing: Enhancing the image clarity through Gaussian filtering and sharpening operations.

2.3. Feature Extraction

This module consists of an encoder and a decoder. During the feature extraction stage, convolution operations in convolutional neural networks (CNN) are employed to extract spatial features of the images. The convolution operation is defined as follows:

Through multiple layers of convolution operations, image features are progressively extracted from low-level features (such as edge information) to high-level features (such as object contours and structural details). During this process, convolutional neural networks are capable of capturing complex patterns in underwater images, effectively enhancing their visual quality.

The input underwater image is first processed by the specially designed Under-Water Net network. The network extracts and processes features through multiple convolutional layers and further optimizes the detail representation of the image via the ARR2ing module. Finally, the enhanced underwater image is generated.

To optimize model performance, we integrate multiple loss functions, including mean squared error (MSE) loss, structural similarity index (SSIM) loss, and peak signal-to-noise ratio (PSNR) loss. By jointly optimizing these loss functions, the network achieves a balance between image sharpness, structural fidelity, and noise control, thereby effectively improving the visual quality of the images.

First, underwater image data with multiple degradation characteristics are extracted from the image dataset; subsequently, normalization operations are performed on the images, and they are converted to a color space suitable for enhancement, such as RGB or HSV.

During the application phase of the enhancement model, the methods we adopt are as follows:

First, we utilize the color correction module to perform equalization adjustment on the RGB channels to achieve color balance; next, through the brightness enhancement module, we apply the CLAHE algorithm to enhance the brightness component, thereby improving the visual effect of the image; finally, in the deblurring module, we estimate the point spread function (PSF) and perform deconvolution operations to restore the image clarity.

To validate the effectiveness of our designed enhancement, the following verifications are conducted:

First, we calculate the PSNR (Peak Signal-to-Noise Ratio) values before and after enhancement, with the formula as follows:

$$\mathrm{PSNR} = 10 \cdot \log_{10}\left(\frac{\mathrm{MAX}^2}{\mathrm{MSE}}\right) \quad (1)$$

Where MAX denotes the maximum possible value of image pixels, and MSE represents the Mean Squared Error of the image. Next, compute the (underwater image quality evaluation) metrics, with the formulas as follows:

$$UCIQE = c_1 \cdot \sigma_c + c_2 \cdot Con_l + c_3 \cdot \mu_s \quad (2)$$

Finally, we compute the (underwater image quality measure), with the formula as follows:

$$UIQM = c_1 \cdot UICM + c_2 \cdot UISM + c_3 \cdot UIConM \quad (3)$$

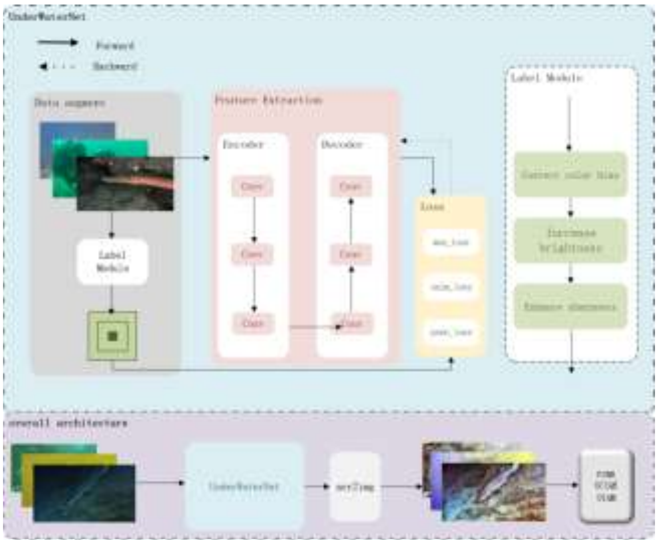

Figure 1 Model structure

2.4. Problem Solving

The steps are as follows:

1. Data Preprocessing: Load the dataset of underwater images and normalize pixel values to [0, 1]. Convert images to the appropriate color space for each enhance-ment technique.

2. Application of Enhancement Modules:

• Color Correction: Apply the color correction module to balance the RGB channels and reduce color cast.

• Brightness Enhancement: Use the CLAHE method to improve brightness and contrast.

•Deblurring: Apply the Wiener filter to restore edge clarity and high-frequency details.

3. Evaluation: Evaluation metrics, including PSNR, UCIQE, and UIQM.

The repaired images and comparison results are shown as Figure 2. From Figure 2, it is evident that the degraded image has been significantly improved after enhancement.

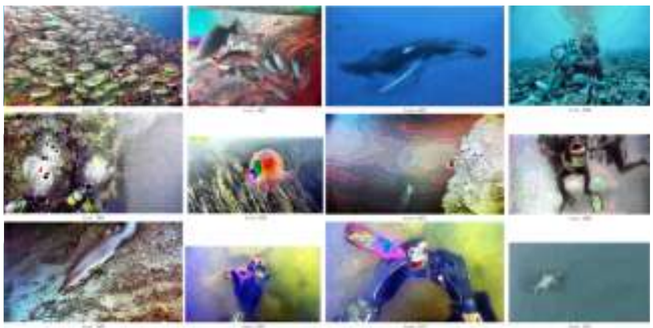

Figure 2 Various Enhancement Result

Through the designed joint enhancement model, the experimental results for processing complex scenes are presented as follows:

(1) Color Correction Effect: For the enhanced images, the color has reached a balanced state, with the mean values of the RGB channels tending toward neutral gray. This significantly reduces the color shift phenomenon, making the image colors more natural and realistic.

(2) Brightness Enhancement Effect: The brightness distribution of the images has been optimized and becomes more uniform. Originally dull details are effectively restored and highlighted, thus making the overall visual effect of the images brighter and clearer.

(3) Deblurring Effect: The edge sharpness of the images has been significantly improved, and high-frequency details are effectively restored. This enables the originally blurred images to present sharper and clearer contours after processing, greatly enhancing the visual quality of the images.

3. Comparative Experiments

To comprehensively evaluate the effectiveness of single enhancement techniques and comprehensive enhancement techniques in addressing underwater image degradation issues, we have designed the following comparative experiments:

(1) Experimental Scheme for Single Enhancement Techniques

In this section, we employ the following single enhancement methods respectively for different types of image degradation:

For the color shift issue, we use color correction technology based on the gray world assumption, with the specific operational formula as follows:

$$\gamma_c = \frac{\mu_{avg}}{\mu_c}, I'_c(x) = \gamma_c \cdot I_c(x) \quad (4)$$

This method aims to adjust the gain of each color channel so that the average color of the image approaches neutral gray, thereby correcting color deviation.

For the low-illumination issue, we use adaptive histogram equalization (CLAHE) technology to enhance image brightness, with the specific operational formula as follows:

$$V'(x) = \text{CLAHE（}V(x) \quad (5)$$

This method aims to effectively improve the visual effect under low-illumination conditions by enhancing the local contrast of the image.

For the image blur issue, we employ non-blind deconvolution technology based on Wiener filtering to perform clarity improvement processing, with the formula as follows:

$$J(x, y) = \mathcal{F}^{-1}\{\frac{\mathcal{F}\{I(x, y) \cdot H^*(u, v)\}}{|H(u, v)|^2 + K}\} \quad (6)$$

(2) Experimental Scheme for Complex Enhancement Techniques

In this section, we utilize the complex enhancement model proposed, which integrates key modules such as data augmentation, feature extraction (including color correction, brightness enhancement, and deblurring processing), and detail optimization.

For image enhancement, we have designed color correction, brightness enhancement, and deblurring processing to perform data augmentation on the input images, with the specific steps as follows:

In the color correction section, we apply histogram equalization to each color channel (RGB) to address the color shift problem.

In the brightness enhancement section, we enhance the image brightness by increasing the brightness value.

In the deblurring processing section, we use Gaussian filtering and sharpening operations to enhance the image clarity.

For optimizing details, we use ARR2ing Module to further optimize the image detail representation, generate the final enhanced underwater image, and combine the loss function to optimize the model performance.

For detail optimization, the ARR2ing Module is employed to further refine theimage details, producing the final enhanced underwater image.

When addressing singular degradation characteristics, single enhancement tech- niques typically achieve higher PSNR values, indicating their effectiveness in restoring image details and clarity.

Comprehensive enhancement techniques, on the other hand, exhibit consistently higher UCIQE and UIQM values in complex degradation scenarios, demonstrating their superior capability in improving overall image quality.

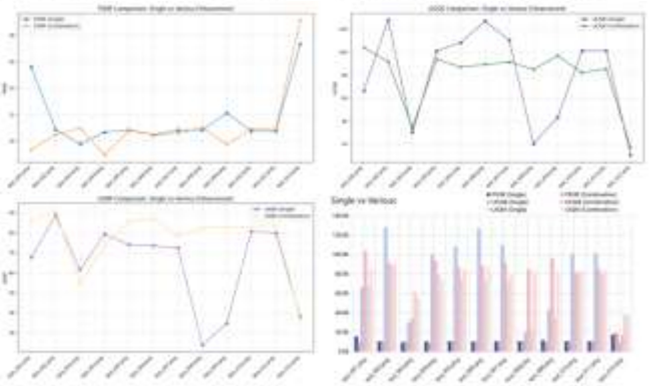

Figure 3 Single and Various Enhancement Comparison

Based on the experimental results, the following recommendations are provided:

1. For scenarios with singular degradation characteristics, single enhancement tech-niques are effective and computationally efficient, making them suitable for tasks requiring quick processing, such as preliminary analysis or real-time monitoring.

2. For scenarios with compounded degradation, comprehensive enhancement tech-niques are preferred, offering balanced improvements across color, brightness, and clarity. These are particularly suitable for applications requiring high image quality, such as underwater object detection and detailed data analysis.

3. In practical applications, the choice of enhancement technique should depend on the specific requirements and constraints of the scenario. For time-sensitive ap-plications, single enhancement techniques are more appropriate, while for tasks requiring high precision and detailed imagery, comprehensive enhancement tech-niques are recommended.

4. Conclusion

This article aims to develop a multifunctional underwater image enhancement model to address various degradation issues such as color shift, low light, and blur in complex underwater environments. This model achieves end-to-end image restoration by integrating preprocessing, data augmentation, and feature extraction modules. The performance of single scene enhancement technology and comprehensive enhancement technology was compared through experiments, and their advantages, limitations, and applicable scenarios were analyzed. Based on experimental data, practical suggestions were proposed.

5. Model Evaluation and Further Discussion

Underwater image enhancement techniques aim to improve underwater image qual-ity, making them clearer, more distinguishable, and aligned with human visual percep-tion.

1. Single Scene Enhancement

Color Cast Correction: Methods like gray-world assumption and white balance adjust RGB channel gains to correct color shifts.

Low Light Enhancement: Techniques like histogram equalization and Con-trast Limited Adaptive Histogram Equalization (CLAHE) improve brightness and contrast.

Deblurring: Wiener filtering and non-blind deconvolution restore clarity by estimating the Point Spread Function (PSF) and reversing convolution effects.

2. Multi-Scene Enhancement

A joint enhancement model integrates color correction, brightness enhance-ment, and deblurring modules to address compounded degradation challenges.

3. Experimental Evaluation

Evaluation Metrics: Metrics such as Peak Signal-to-Noise Ratio (PSNR), Underwater Color Image Quality Evaluation (UCIQE), and Underwater Image Quality Measure (UIQM) are used to quantify the quality and visual effects of enhanced images.

Experimental Results: Comprehensive enhancement techniques demon-strate superior performance in complex scenarios, while single enhancement techniques are effective for specific types of degradation.

6. Future Prospects

Underwater image enhancement techniques play a critical role in improving image quality for underwater exploration and research. Future advancements can focus on the following directions:

•Preprocessing Enhancements: Standardize image dimensions before data aug-mentation to ensure consistency, and integrate denoising modules post-augmentation to further improve image quality.

• Deep Learning Optimization: Incorporate advanced deep learning models, such as attention mechanisms and dilated convolutions, to enhance precision and feature extraction while reducing computational overhead.

• Multi-Source Data Fusion: Leverage data from sonar, LiDAR, and other modal-ities to improve robustness and accuracy through multi-task learning and collabo-rative processing.

• Real-Time Processing: Develop algorithms capable of real-time enhancement to support dynamic underwater monitoring and analysis.

•Application Expansion: Extend the application of enhancement techniques to areas such as robotic navigation, target tracking, and environmental modeling to support diverse underwater research needs[3].

• Efficiency Improvements: Design adaptable methods for varying underwater conditions, ensuring scalability for high-resolution imaging and compatibility with advanced systems such as autonomous underwater vehicles (AUVs).

By focusing on these directions, underwater image enhancement techniques can continue to enable clearer and more detailed imaging, driving progress in fields like environmental monitoring, resource exploration, and marine biology.

References

[1] Pham, Nguyen-Hoang-Hai and Sun, Chi-Chia, ”FPGA-Based Single Image Dehaz-ing System Implementation Using Improved Dark Channel Prior,” 2023 IEEE 12th Global Conference on Consumer Electronics (GCCE), pp. 749-750, 2023.

[2] Chen, Peng, Jamet, C´edric, and Liu, Dong, ”LiDAR Remote Sensing for Vertical Distribution of Seawater Optical Properties and Chlorophyll-a From the East China Sea to the South China Sea,” IEEETransactions on Geoscience andRemote Sensing, vol. 60, pp. 1-21, 2022.

[3] Fan, Junfeng, Wang, Xuan, Zhou, Chao, Ou, Yaming, Jing, Fengshui, and Hou, Zengguang, ”Development, Calibration, and Image Processing ofUnderwater Struc-tured Light Vision System: A Survey,” IEEE Transactions on Instrumentation and Measurement, vol. 72, pp. 1-18, 2023.

[4] Tarekegn, Adane Nega, Cheikh, Faouzi Alaya, Ullah, Mohib, Sollesnes, Erik Tobias, Alexandru, Cornelia, Azar, Saeed Nourizadeh, Erol, Erdeniz, and Suciu, George,” Underwater Object Detection using Image Enhancement and Deep Learning Mod-els,” 2023 11th European Workshop on Visual Information Processing (EUVIP), pp. 1-6, 2023.