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Aquavision Alchemy Illuminating Underwater Imagery Through Medium Transmission

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Abstract - Restoring underwater scenes often involves addressing interference caused by the underwater environment. Many existing methods overlook the scale-related characteristics inherent in these scenes. To tackle this, we propose a synergistic multi-scale detail refinement method for enhancing underwater scene details. This approach comprises multiple stages, starting with a low-degradation stage that enriches original images with multi-scale details using the Adaptive Selective Intrinsic Supervised Feature module. ASISF, through intrinsic supervision, precisely manages feature transmission across different degradation stages, refining multi-scale details while minimizing irrelevant information. Within the framework, we introduce the Bifocal Intrinsic-Context Attention Module, which efficiently utilizes multi-scale scene information by leveraging spatial contextual relationships. Throughout training, a multi-degradation loss function enhances the network's ability to extract information across various scales. The proposed method consistently outperforms state-of-the-art methods when evaluated against them.

***Key Words*:** Interference mitigation, Multi-scale detail refinement, Intrinsic supervision, Spatial contextual relationships.

INTRODUCTION

The quality of optical images in underwater environments is largely determined by the impact of dissolved and suspended substances on light absorption and scattering. Absorption effects present challenges such as reduced imaging distance and color distortion, while scattering effects diminish image contrast and detail. Our objective is to improve the quality of underwater optical images, offering robust solutions for various applications including underwater exploration, marine biology research, and surveillance. Image enhancement techniques empower researchers and practitioners to better interpret and analyze underwater image data.

Enhancing low-quality images in this context presents significant challenges to the field of computer vision. These challenges primarily stem from scattering and blurring effects unique to aquatic environments, which manifest in a multi-scale manner. Particulate matter and water turbulence at different scales exert distinct effects on various parts of an image, leading to the degradation of multi-scale correlated features. The underwater image formation model can be represented as follows:.

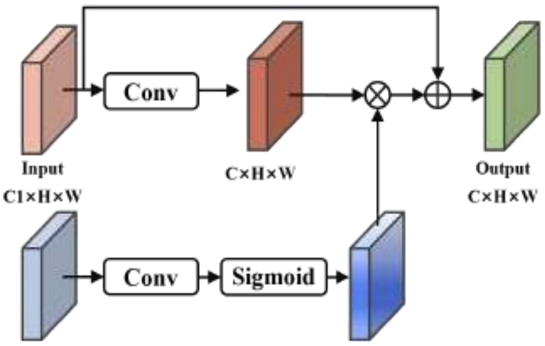
$$I = J \times t + A(1 - t) \qquad (1)$$

The core objective of underwater image enhancement is to accurately estimate the clear image from the underwater image considering the transmission related to depth and atmospheric light. This estimation is crucial as degradation levels in underwater images can vary significantly across pixels due to differences in depth. Various existing enhancement techniques either globally or locally extract features and leverage filters and color correction techniques to enhance image quality. However, the inherent scale-related characteristics in underwater scenes demand attention, as pixels at similar depths often exhibit consistent degradation levels. Recognizing these depth-informed degradation patterns can provide a richer understanding of the scene structure.

To address these challenges, we propose the Synergistic Multiscale Detail Refinement via Intrinsic Supervision for Underwater Image Enhancement. This approach uniquely leverages low-resolution images as auxiliary inputs to gain additional insights into scene degradation. By integrating features from both low-degradation and original images, we enhance credibility and applicability while excluding irrelevant information from the original resolution using the Adaptive Selective Intrinsic Supervised Feature module.

Methodology

Our proposed model incorporates four stages of multi-resolution image inputs, providing the network and associated features with a variety of scale scene information from the input image. Initially, we utilize downsampling on the original image to generate underwater scenes of various scales.



The bifocal intrinsic-context attention module, depicted in Figure 3, comprises two distinct branches. The first branch is responsible for recognizing the significant influence of neighboring pixel regions for image restoration. This branch includes the Comprehensive Feature Attention module, followed by the Resolution-Guided Intrinsic Attention module. The Comprehensive Feature Attention module extracts features from pixels and channels using spatial attention and channel attention, respectively. These features are then passed to the Resolution-Guided Intrinsic Attention module, which aims to broaden the receptive field while maintaining computational efficiency. Employing low-resolution spatial intrinsic supervision, the Resolution-Guided Intrinsic Attention module can further enhance features by effectively capturing multi-scale scene details.

Underwater image optimization heavily relies on the contextual details of neighboring pixels. However, to manage network complexity, enhancement methods often employ compact 3×3 convolutional kernels for feature extraction. While 3×3 kernels are computationally efficient, their small receptive field limits the network's ability to capture extensive contextual nuances.

To overcome this limitation and broaden the receptive field, we introduce the Resolution-Guided Intrinsic Attention Module. ReGIA enhances the initial features extracted from the input image by the Comprehensive Feature Attention module. It is designed to discern feature weight data in a lower-resolution latent space with a wider receptive field. By expanding the receptive field of convolutional kernels, ReGIA acts as a guiding beacon that not only enhances the correlation of features in the original domain but also learns features from its larger contextual receptive field.

To effectively integrate feature information from the low-resolution encoder and decoder into the original resolution branch while mitigating interference from non-essential information during image restoration, we introduce the Adaptive Selective Intrinsic Supervised Feature Module. This module employs an intrinsic-supervised approach for feature selection and constraint, as illustrated in Figure 3.

Testing

In this section, we utilized both objective assessments (including UIQM, UCIQE, CCF, CEIQ, VSI, PSNR, MSE, SSIM, FSIM, and FSIMc) and subjective evaluations for a comprehensive analysis.

Experiments were conducted to compare the effectiveness of various state-of-the-art methods, encompassing both traditional methods (such as ULAP, IBLA, GDCP) and deep learning methods (such as WaterNet, FUnIEGAN, UWCNN, UColor, UDA, and U-shape). Visual results are depicted in Figure 4, while metric comparisons are presented in Table 1.

Table -1: Sample Table format

Dataset	Metric	ULAP	IBLA	GDCP	WaterNet	FUnIE GAN	UWCNN	UColor	UDA	U-shape	SMDR-IS
UIEB Val	PSNR ↑	15.913	17.988	13.386	17.349	17.114	17.985	20.962	21.484	20.462	**23.710**
	MSE ↓	0.174	0.143	0.228	0.144	0.150	0.134	0.097	0.096	0.100	**0.075**
	SSIM ↑	0.745	0.805	0.747	0.813	0.701	0.844	0.863	0.873	0.792	**0.922**
	VSI ↑	0.947	0.958	0.943	0.966	0.941	0.966	0.971	0.970	0.959	**0.983**
	FSIM ↑	0.915	0.928	0.901	0.908	0.891	0.923	0.931	0.932	0.892	**0.967**
	FSIMc ↑	0.878	0.899	0.865	0.899	0.858	0.903	0.920	0.918	0.883	**0.957**
	UIQM ↑	2.259	2.490	2.670	2.917	3.092	3.011	3.049	2.897	3.131	**3.015**
	UCIQE ↑	0.604	0.606	0.592	0.606	0.564	0.554	0.591	**0.612**	0.576	0.607
	CCF ↑	24.145	23.841	23.026	20.042	20.416	20.360	21.827	**26.220**	21.966	26.012
	CEIQ ↑	3.209	3.283	3.208	3.101	3.307	3.090	3.209	**3.372**	3.235	3.369
	ALL ↑	49.441	51.656	46.109	47.455	47.733	48.502	53.226	58.374	52.997	**60.466**

Competence

Table 2 presents a comprehensive analysis of efficiency, performance (where "Quality" represents the "ALL" value in the UIEB Val column in Table 1), and Aggregative (Agg) score. Although not achieving the highest efficiency, it still achieves a commendable frame rate of 16.4744 FPS, meeting real-time demands. Additionally, the introduction of the Agg score provides a holistic performance evaluation, considering both efficiency and performance, specifically, Agg = Quality-Time. As observed from Table 2, the method achieves the highest score in Agg, demonstrating its suitability for advanced underwater vision tasks.

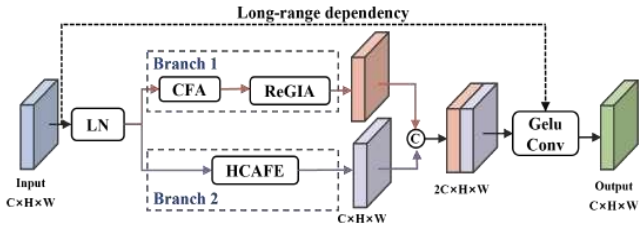


Fig -1: Figure

Charts

	ULAP	IBLA	GDCP	WaterNet	FUnIEGAN	UWCNN	UColor	UDA	U-shape	SMDR-IS
Time ↓	0.358	9.134	0.163	0.091	**0.003**	0.050	0.577	0.100	0.109	0.061
Quality ↑	49.441	51.656	46.109	47.455	47.733	48.502	53.226	58.374	52.997	**60.466**
Agg ↑	49.083	42.522	45.946	47.364	47.730	48.452	52.649	58.273	52.887	**60.405**

CONCLUSIONS

In this study, we propose a method for underwater image restoration that efficiently captures multi-scale scene information through multi-resolution detail extraction with intrinsic supervision. Leveraging the inherent scale-related features in image scenes, we integrate low-resolution inputs alongside original-resolution input to enhance the conveyance of scene information. Additionally, our multi-degradation loss function strategically guides the network during training, enhancing its ability to leverage information at different scales. Overall, our approach adeptly exploits multi-scale nuances to enrich scene information in underwater imagery. In the future, we plan to explore integrating this method into broader computer vision applications such as underwater robotics and autonomous underwater vehicles.

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