Lightweight Underwater Image Enhancement via Impulse Response of Low-Pass Filter based Attention Network

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Outline

2

Introduction

- Decline in underwater image quality has constrained the accurate visual for diverse ocean engineering and scientific research.
- Image quality affects object classification, saliency detection, marine monitoring, and target detection.
- Key challenges: light intensity, scattering, and turbidity in underwater environments.

Impact of Scattering & Absorption

- Scattering and absorption reduce contrast and cause color distortion.
- Scattering: Particles like solids, plankton, and dust disperse light.
- Absorption: Higher for red light, giving images a blue-green tone.

3

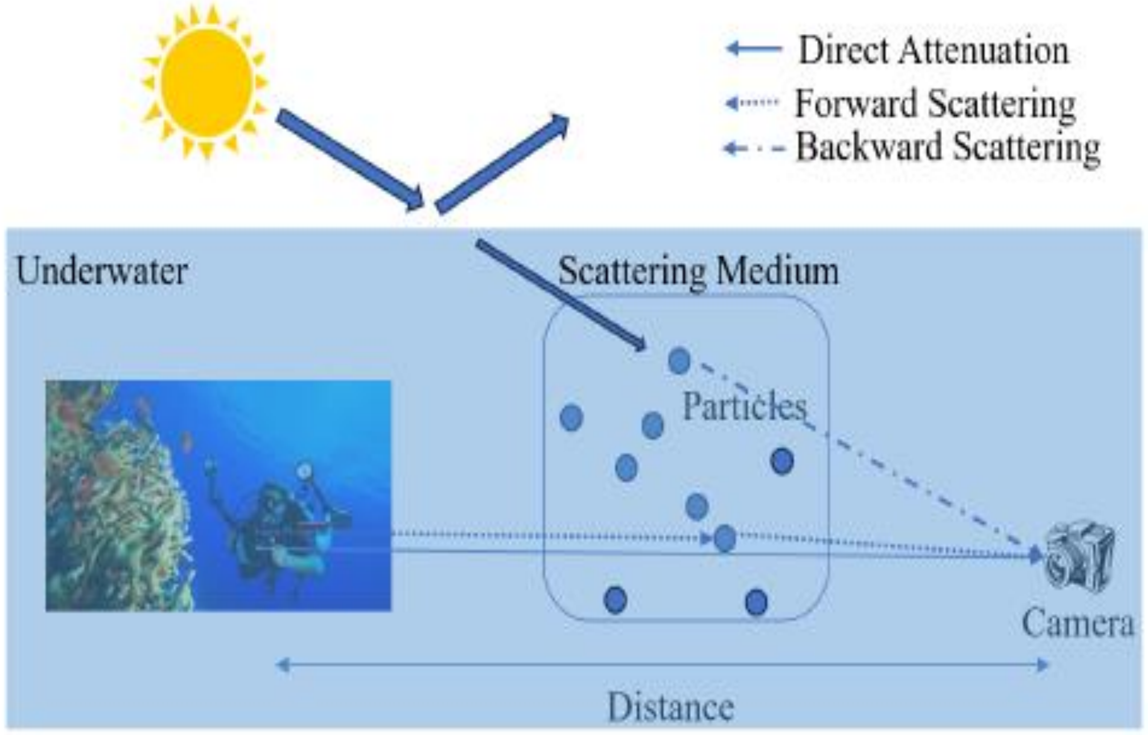


Fig 1. Schematic diagram of underwater imaging

Existing Approaches to Underwater Image Enhancement

Enhancement methods classified into:

1. Non-physical model-based
2. Physical model-based
3. Data-driven

Specialized Models for Underwater Image Enhancement

- **Deep SESR**: Improves super-resolution using dense blocks and attention networks.
- **iDehaze**: Two-step approach for dehazing and color correction.
- **MDCNN-VGG**: Adapts to multi-domain underwater images but faces issues with detail preservation.
- **Shallow-UWnet** : Lightweight model with fewer parameters and faster computation and suited for portable AUVs due to low resource demands. Then, it improved color correction with reduced testing time.

4

Objectives

✓To enhance poor visibility caused by light attenuation, absorption, and scattering.

✓To reduce noise caused by suspended particles in underwater environments.

✓To create a lightweight model suitable for energy-limited AUVs and ROVs.

✓To improve generalization ability across diverse underwater scenes.

✓To enhance image quality without adding computational overhead.

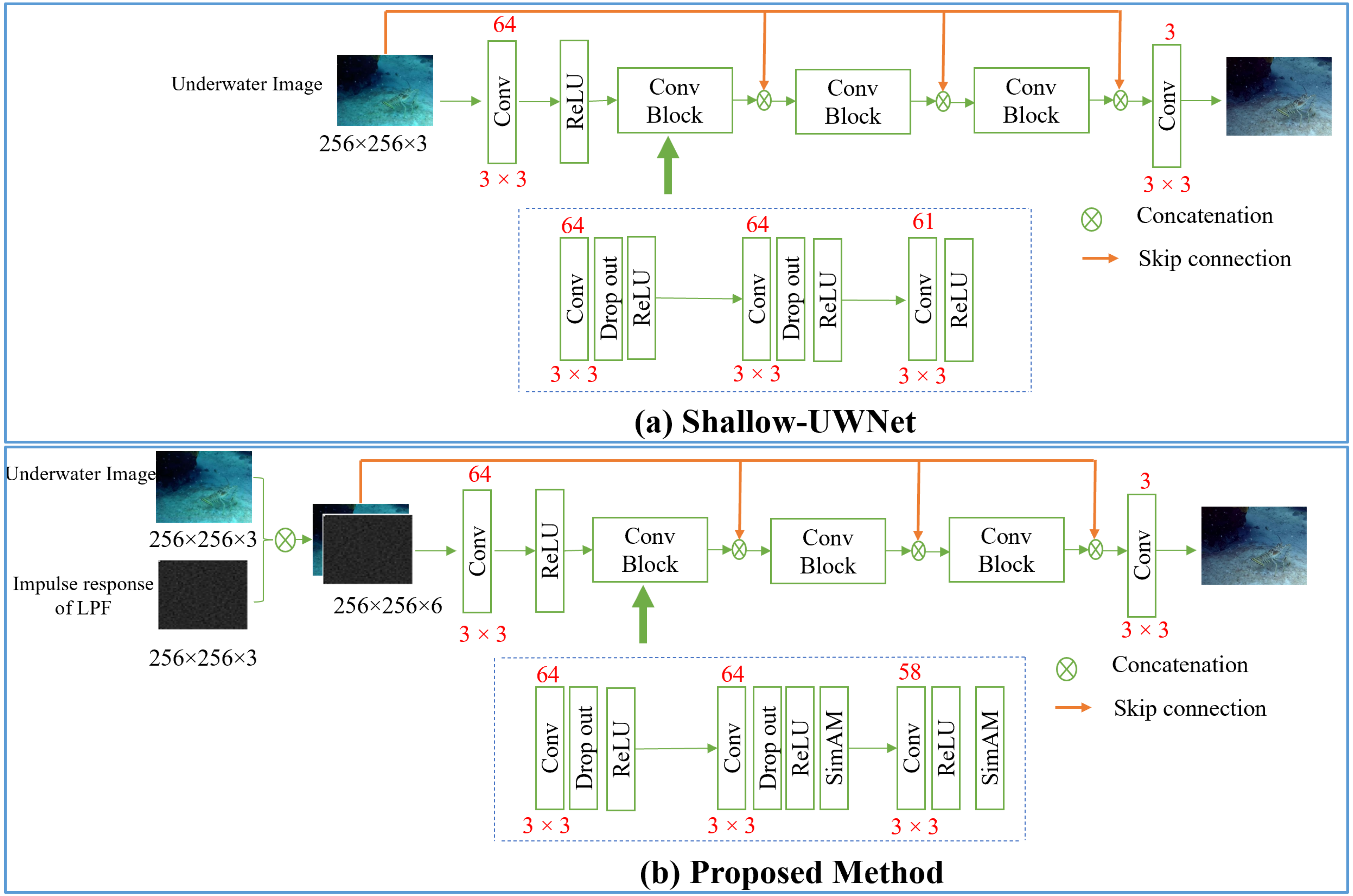
Contribution

✓**Skip Connection** : To solve the vanishing gradient problem by concatenating raw underwater images with impulse response of low-pass filter images.

✓**Attention Module** : Integrates a simple, parameter-free attention module (SimAM) into each convolution block to enhance the generalization ability of the model.

Methodology

Proposed Method



(a) Shallow-UWNet

(b) Proposed Method

Proposed Method

The impulse response of power spectrum sparsity low-pass filter (SLPF) is constructed by:

✓Compute power spectrum

$$P(\omega_1,\omega_2) = |X(\omega_1,\omega_2)|^2$$

where $X(\omega_1,\omega_2)$ is the Fourier transform of image.

✓Calculate power spectrum sparsity $S = \frac{P_a}{P_h + P_v}$

Where:

P_a = Overall power spectrum values

P_h = Horizontal power spectrum values at the center

P_v = Vertical power spectrum values at the center

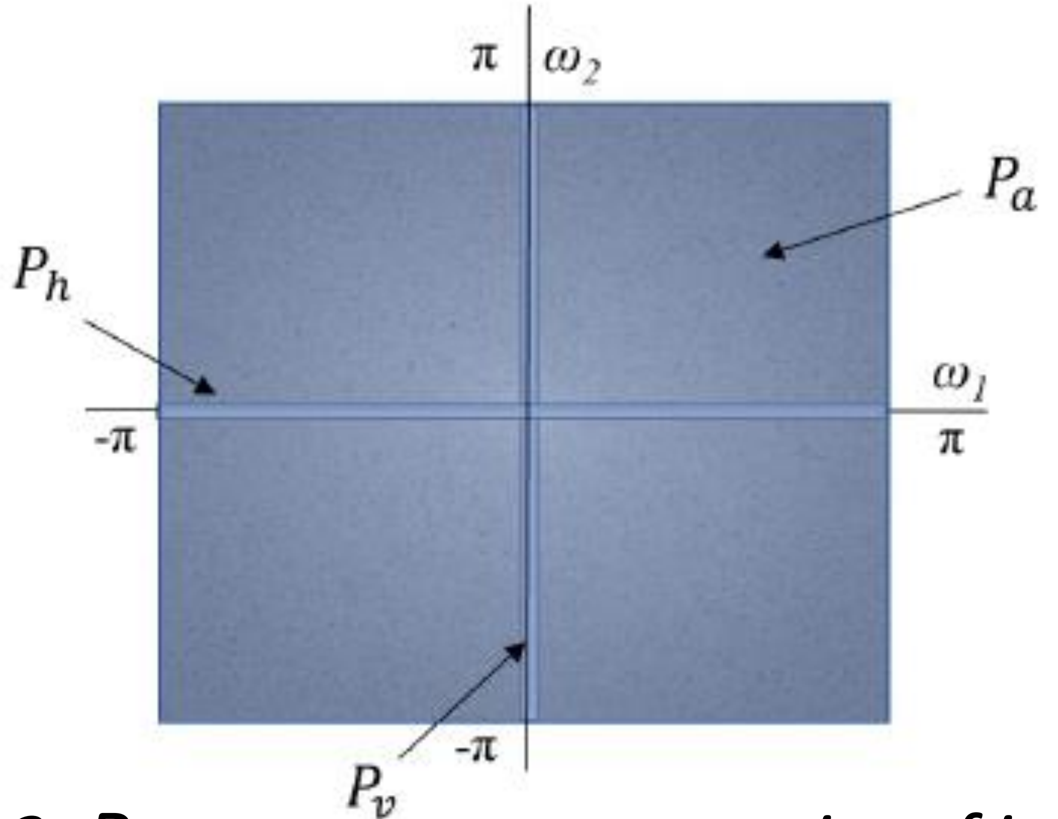


Fig 3. Power spectrum sparsity of image

Proposed Method

✓Set Threshold $\gamma = \lambda S$

where λ is a scaling parameter.

✓Design frequency response, $H_S\,(\omega_1, \omega_2)$:

$$H_s(\omega_1, \omega_1) = \begin{cases} 1, & if\ H_s(\omega_1, \omega_1) \leq \gamma \\ 0, & otherwise \end{cases}$$

✓Compute inverse Fourier transform (IFFT) of $H_S\,(\omega 1, \omega 2)$ to obtain the spatial domain image.

SimAM (Simple, parameter- free attention module)

10

✓A non-parametric, energy-based attention mechanism that generates 3D weights. The minimum energy neuron is calculated as :

$$\epsilon_T = \frac{4(\rho^2 + \alpha)}{(T - \eta)^2 + 2\rho^2 + 2\alpha}$$

Where T is the target neuron, ϵ_T represents the lower energy neuron , η and ρ^2 is the mean and variance of neurons.

Experimental Results

Proposed Model Training Configuration

Training Settings

- Optimizer: ADAM optimizer with a learning rate of 0.0002.
- Dropout Rate: 0.2 to prevent overfitting.
- Batch Size: 1, with 50 epochs to ensure thorough training.
- Input Image Size: Resized to 256×256 pixels for consistency.

Framework & Hardware

- Framework: Model is developed in PyTorch. 12
- Hardware: Trained on Intel Core i9 CPU, Nvidia GeForce RTX 4070 GPU, and 32GB RAM.

Dataset Information

1. **EUVP Dataset**: Contains images from seven distinct cameras used in deep-sea exploration and human-robot studies. Utilized 3,500 image pairs for training and 200 pairs for validation. EUVP-Dark used as a testing dataset, capturing 1,000 dark-hazed images for evaluating model performance on challenging visibility conditions.

2. **UIEB Dataset:** Contains 890 real-world underwater images with varied distortion, light conditions, colors, and contrast levels. Reference images are color-accurate and free from color casts.

3. **UFO-120 Dataset**: High-quality images from oceanic exploration, with distorted images created through style transfer. Provides 120 paired images as a benchmark for enhancement tasks.

Image Quality Assessment (IQA)

Reference IQA

- **PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index)** assess the difference between enhanced underwater images and their reference images.
- Obtaining ideal reference images for underwater conditions is impractical.

Non-Reference IQA

- **UIQM (Underwater Image Quality Measure):** Designed to evaluate image quality without needing reference images, inspired by human visual perception.
- Higher UIQM values indicate images with better color saturation, contrast, and overall similarity to human visual perception, making it a key metric for non-reference evaluation.

14

Experimental Results

Table 1 : Quantitative comparisons (PSNR, SSIM and UIQM) on EUVP_Dark, UFO_120 and UIEB datasets [Bold : Best, Underline Second Best]

Method	Dataset								
	EUVP-Dark			UFO-120			UIEB		
	PSNR	SSIM	UIQM	PSNR	SSIM	UIQM	PSNR	SSIM	UIQM
WaterNet[5]	24.43±4.6	0.82±0.08	2.97±0.32	23.12±3.3	0.73±0.07	2.94±0.38	19.11±3.7	<u>0.79±0.09</u>	<u>3.02±0.34</u>
FUnIE-GAN [6]	26.19±2.9	0.82±0.08	2.84±0.45	24.72±2.6	<u>0.74±0.06</u>	2.88±0.41	19.13±3.9	0.73±0.11	2.99±0.39
UGAN [7]	26.53±3.1	0.80±0.05	2.89±0.43	24.23±3.0	0.69±0.07	2.54±0.45	-	-	-
DeepSESR [8]	25.30±2.6	0.81±0.07	2.95±0.32	**26.46±3.1**	**0.78±0.07**	<u>2.98±0.37</u>	19.26±3.6	0.73±0.11	2.95±0.39
iDehaze [9]	23.01±2.0	0.84±0.09	**3.11±0.36**	17.55±1.9	0.72±0.07	**3.29±0.26**	17.96±2.8	**0.80±0.07**	**3.28±0.33**
MDCNN-VGG [10]	27.49	0.82	<u>3.0</u>	<u>25.27</u>	0.74	2.88	19.09	0.75	2.80
Xing et.al [12]	**33.45±4.2**	**0.89±0.09**	2.98±0.37	24.35±3.0	0.72±0.08	2.85±0.37	<u>19.71±4.0</u>	0.71±0.13	2.71±0.45
Shallow-RepNet [13]	24.49±2.5	0.79±0.06	2.82±0.29	22.32±2.4	0.72±0.07	<u>2.98±0.33</u>	**19.80±2.8**	0.77±0.08	2.79±0.32
Shallow-UWnet [11]	27.86±3.1	<u>0.85±0.04</u>	2.93±0.40	25.07±2.9	<u>0.74±0.08</u>	2.87±0.39	19.01±3.6	0.68±0.14	2.79±0.44
Proposed (SLPF)	27.87±3.0	0.84±0.05	2.96±0.36	<u>25.27±2.8</u>	0.73±0.08	2.90±0.36	19.14±3.7	0.69±0.13	2.84±0.41
Proposed (DLPF)	<u>27.89±3.1</u>	0.84±0.05	2.98±0.35	25.23±2.9	0.73±0.08	2.91±0.36	19.17±3.6	0.69±0.13	2.85±0.41
Proposed (GLPF)	27.87±3.0	<u>0.85±0.05</u>	2.95±0.37	25.25±2.9	<u>0.74±0.08</u>	2.89±0.37	19.08±3.6	0.69±0.13	2.82±0.42
Proposed (BLPF)	27.77±3.0	0.84±0.05	2.96±0.35	25.22±2.9	0.73±0.08	2.90±0.36	19.10±3.6	0.68±0.13	2.83±0.41

Experimental Results

Table 2 : Performance metrics of model lightweight [Bold : Best, Underline : Second Best]

Metrics	Number of parameters	Testing per image (sec)
WaterNet [5]	1,090,688	0.5
FUnIE-GAN [6]	4,212,707	0.18
Deep SESR [8]	2,454,023	0.16
Xing et.al [12]	219,840	**0.02**
Shallow-UWnet [11]	<u>219,456</u>	<u>0.04</u>
Proposed (SLPF)	**216,000**	0.05
Proposed (DLPF)	**216,000**	0.2
Proposed (GLPF)	**216,000**	0.3
Proposed (BLPF)	**216,000**	0.3

Experimental Results

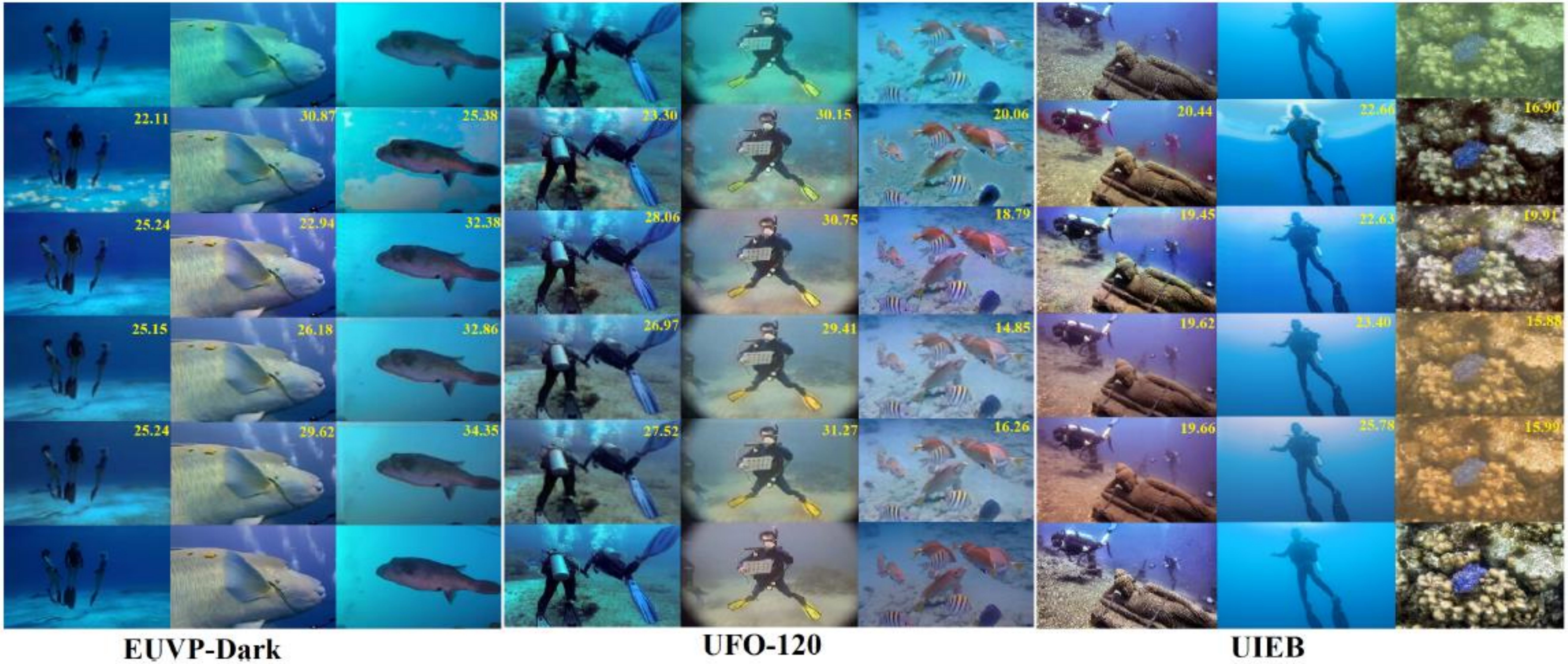


Fig 4. Comparison of different methods on the EUVP_Dark, UFO_120, and UIEB datasets [from top to bottom] Raw Input Image, WaterNet, FUnIE-GAN, Shallow-UWnet , Proposed method (SLPF) and Ground Truth

Conclusion

- Developed a lightweight, compressed model for underwater image enhancement.
- Integrated SimAM (Simple Attention Mechanism) and skip connections to combine the raw underwater image with the impulse response of LPF (Low-Pass Filter), enhancing the conventional Shallow-UWnet architecture.

Key Benefits:

- Better adaptability to unseen underwater features by combining SimAM and skip connections.
- Outperforms Shallow-UWnet in PSNR and UIQM metrics.

- Achieves high-quality enhancement with fewer trainable parameters and faster processing, making it suitable for real-time applications.
- Ideal for deployment on resource-constrained underwater robots in real-time exploration.

18

Thank You