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

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Background

- ✓ Decline in underwater image quality has constrained the accurate visual for diverse ocean engineering and scientific research.

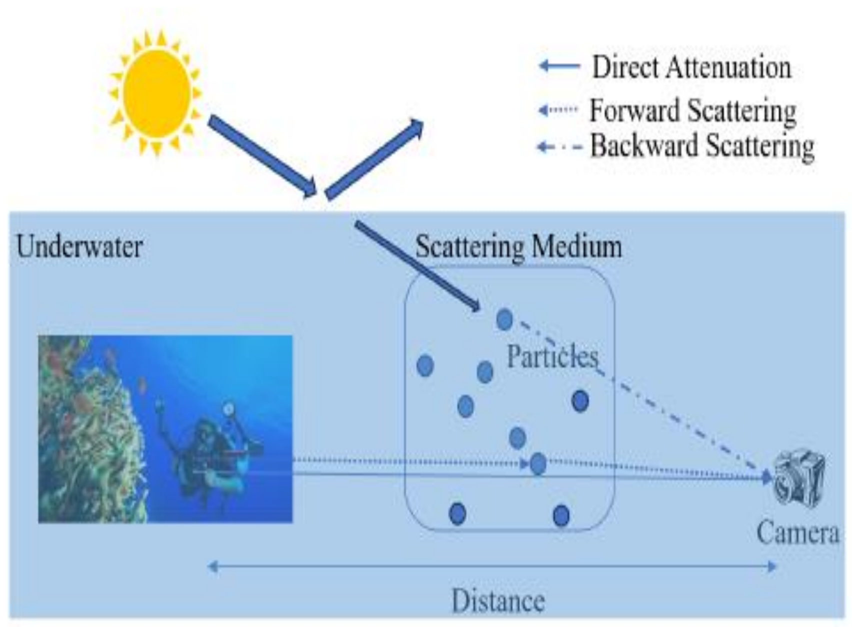

Fig 1. Schematic diagram of underwater imaging

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.

Contributions

- ✓ **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

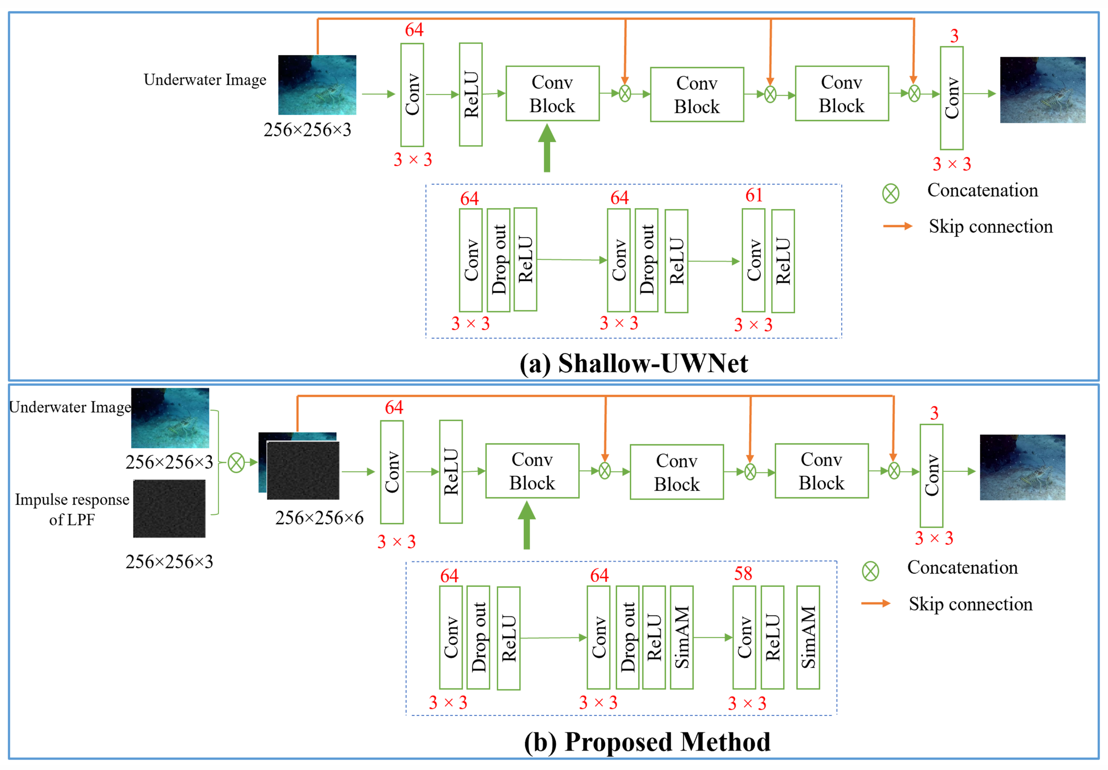

Fig 2. Architectures of (a) Shallow_UWNet and (b) proposed method

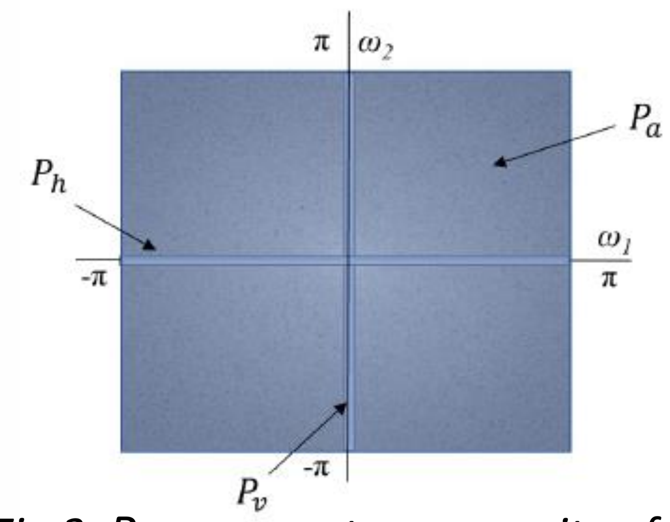

Fig 3. Power spectrum sparsity of image

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

- ✓ Set Threshold $\gamma = \lambda S$

where λ is a scaling parameter.

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

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

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

SimAM (Simple, parameter- free attention module)

- ✓ 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.

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	0.79±0.09	3.02±0.34
FUnIE-GAN [6]	26.19±2.9	0.82±0.08	2.84±0.45	24.72±2.6	0.74±0.06	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**	2.98±0.37	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	3.0	25.27	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	19.71±4.0	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	2.98±0.33	**19.80±2.8**	0.77±0.08	2.79±0.32
Shallow-UWnet [11]	27.86±3.1	0.85±0.04	2.93±0.40	25.07±2.9	0.74±0.08	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	25.27±2.8	0.73±0.08	2.90±0.36	19.14±3.7	0.69±0.13	2.84±0.41
Proposed (DLPF)	27.89±3.1	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	0.85±0.05	2.95±0.37	25.25±2.9	0.74±0.08	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

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]	219,456	0.04
Proposed (SLPF)	**216,000**	0.05
Proposed (DLPF)	**216,000**	0.2
Proposed (GLPF)	**216,000**	0.3
Proposed (BLPF)	**216,000**	0.3

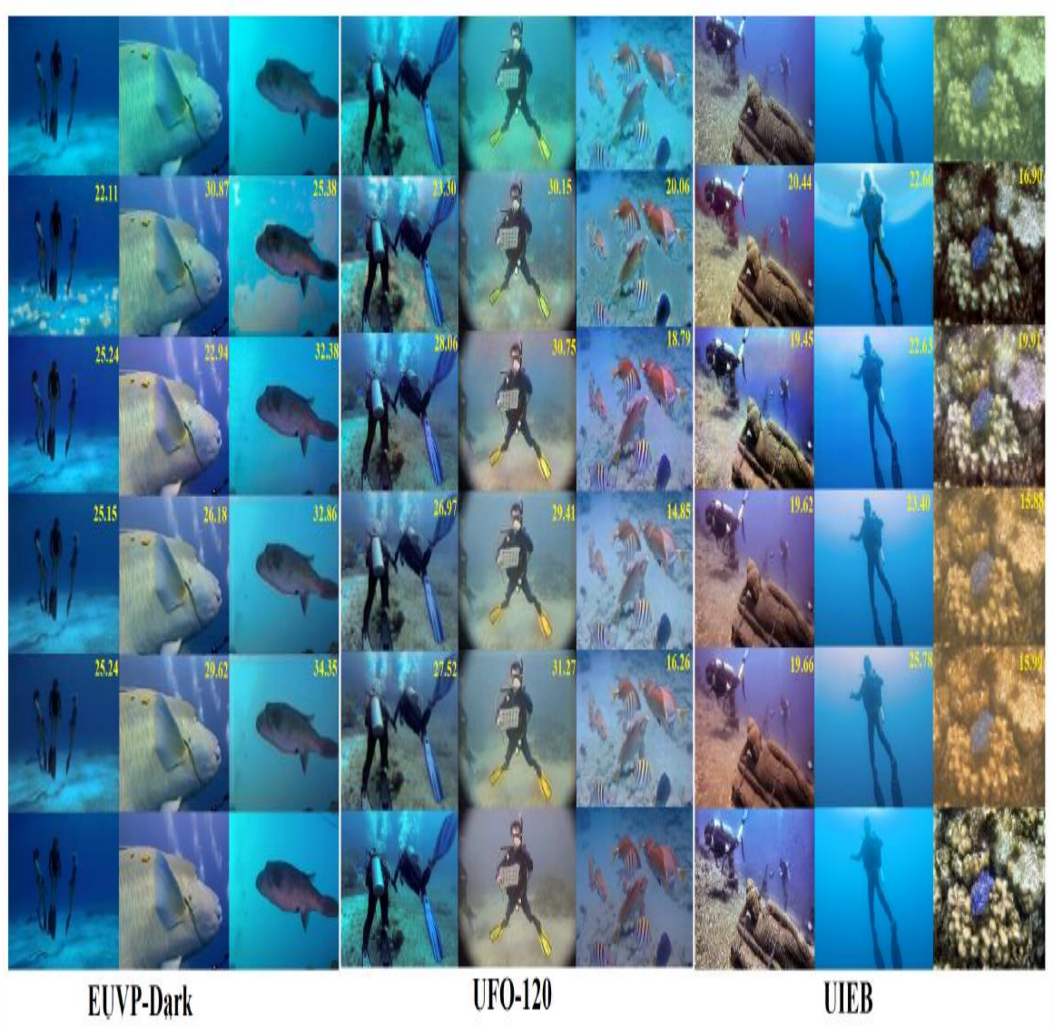

Fig 4. Comparison of different methods on the EUVP_Dark, UFO_120, and UIEB datasets [from top to bottom] Raw Input Image, WaterNet, FUnIE-GAN, Shallow-UWnet , Proposed method (SLPF) and Ground Truth

Conclusion

- ✓ Outperforms conventional Shallow_UWnet in PSNR and UIQM metrics.
- ✓ Fewer trainable parameters and faster testing time.
- ✓ Suitable for real-time applications in resource-constrained underwater robots, such as AUVs and ROVs.