Re-Degradation and Contrastive Learning for Zero-shot Underwater Image Restoration

Supplementary material

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The figures and tables in this supplementary material are numbered using the prefix S, and are arranged as follows:

1. The detailed network architecture of the proposed UWZR.
2. Selection of α and β for re-degradation.
3. Execution time analysis.
4. Additional qualitative and quantitative results.

S1. Network Architecture

The detailed structure of each block of UWZR is given in Table S1. Input UW image I is disentangled into global background light (A), transmission maps corresponding to direct signal (T_D) and back-scatter (T_B) using A-Net, TM-Net_D, and TM-Net_B, respectively. Following [7], we estimate a 3-dimensional output vector corresponding to the global background light in the (R, G, B) channels using A-Net. We use the same network structure for both TM-Net_D and TM-Net_B to estimate T_D and T_B, respectively. The output transmission maps have the same size as the input UW image. We only work in the input image scale, unlike [7] where they utilize the output from a multi-scale feature selection module for the estimation of both the transmission map and global background light. For HF-Net, we use a regression network that predicts a 64-dimensional output from the features extracted from the input image patch using a network with a similar structure as that of A-Net.

S2. Selection of α and β for re-degradation

As discussed in Section 3.1, for re-degradation, we use a known ratio (α, β): $\alpha \in (0,1)$, $\beta \in (0,1)$, and $(\alpha+\beta) < 1$. To study the effect of the selection of α and β on the performance of UWZR, we choose different combinations of α and β both vary from 0.1 to 0.8 with a step size of 0.1. We calculate the average PSNR values on the restored outputs for HICRD [6] dataset for each combination of α and β and are plotted in Fig. S1. PSNR values differ slightly for different combinations, but the standard deviation is only 0.56 dB. Hence, there is negligible dependency on the values of α and β.

S3. Execution time

We perform experiments on a PC with an NVIDIA GeForce RTX3090 GPU. For images from different datasets (UIEB [9], HICRD [6], RUIE [10], and SQUID [1]), the total loss calculated in every epoch during training is plotted in Fig. S2. It can be seen that, for every dataset, UWZR converges before epoch 500. Hence, we limit the number of epochs to 500. The execution time of UWZR for an image of size 544 × 294 is 26 seconds.

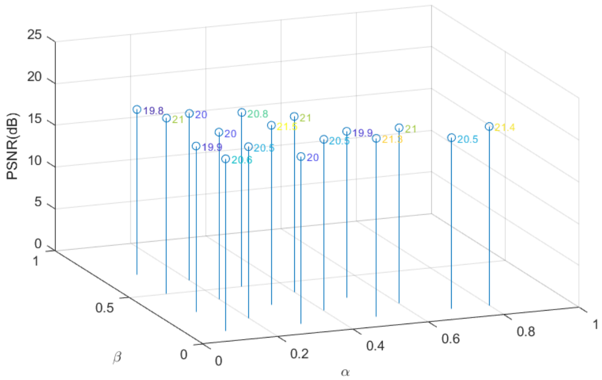

Figure S1: PSNR obtained for the HICRD [6] dataset for different combinations of α and β.

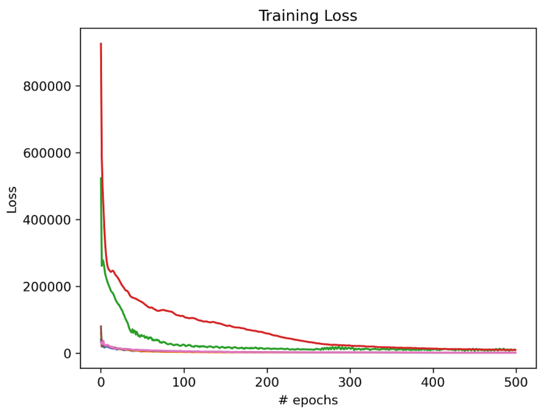

Figure S2: Training loss curve.

S4. Additional qualitative results

Additional results for comparing image restoration performance on images from 4 datasets (HICRD [6], UIEB [9], RUIE [10], and SQUID [1]) are included in Fig. S3. It can be seen that UW provides more realistic restored outputs without color deviations. For UIEB [9] and HICRD [6] datasets, outputs from UWZR are close to ground truth. For RUIE [10] and SQUID [1], our outputs are visually good. Even though supervised networks (Waternet [9], UIEC^2-Net [13], and PUIE-Net [4]) work very well for UIEB [9] dataset (on which they are trained), their performance on other datasets is not good. Outputs of traditional methods (GDCP [12], IBLA [11], and Histogram prior [8]) have color artifacts. Performance of the unsupervised method USUIR [3] is not satisfactory. Outputs of other zero-shot methods

Layer	Input	Block Structure	Config.	Output
A-Net				
Input	I_1	-	c:3	out_1
Block 1	out_1	[Conv, Group Norm., ReLU]	k: 9, s: 4, c: 64	out_2
Block 2	out_2	[Conv, Group Norm., ReLU]	k: 3, s: 1, c: 64	out_3
Block 3	out_3	[Maxpool]	k: 15, s: 7, c: 64	out_4
Block 4 to 5	out_4	[Conv, Group Norm., ReLU] x2	k: 3, s: 1, c: 64	out_5
Block 6	out_5	[Global Avg pool]	n: 64	out_6
Output	out_6	[Sigmoid]	n: 3	A
TM-Net$_\mathbf{D}$/TM-Net$_\mathbf{B}$				
Input	I_1	-	c:3	out_1
Block 1	out_1	[Conv, Group Norm., ReLU]	k: 9, s: 2, c: 64	out_2
Block 2	out_2	[Conv, Group Norm., ReLU]	k: 3, s: 1, c: 64	out_3
Block 3 to 4	out_3	[Conv, Group Norm., ReLU] x2	k: 3, s: 1, c: 64	out_4
Block 5	out_4	[Upsample $\times$ 2]	c: 64	out_6
Output	out_6	[Conv, Sigmoid]	c: 3, k: 3, s: 1	T_D/T_B
HF-Net				
Input	I_1	-	c:3	out_1
Block 1	out_1	[Conv, Group Norm., ReLU]	k: 9, s: 4, c: 64	out_2
Block 2	out_2	[Conv, Group Norm., ReLU]	k: 3, s: 1, c: 64	out_3
Block 3	out_3	[Maxpool]	k: 15, s: 7, c: 64	out_4
Block 4 to 5	out_4	[Conv, Group Norm., ReLU] x2	k: 3, s: 1, c: 64	out_5
Block 6	out_5	[Global Avg pool]	n: 64	out_6
Output	out_6	[Sigmoid]	n: 64	X

Table S1: Network structure of UWZR. [c: number of output channels in the block, k: kernel size, s: stride, n: number of output nodes, Group Norm.: Group normalization], Upsample using bilinear interpolation.

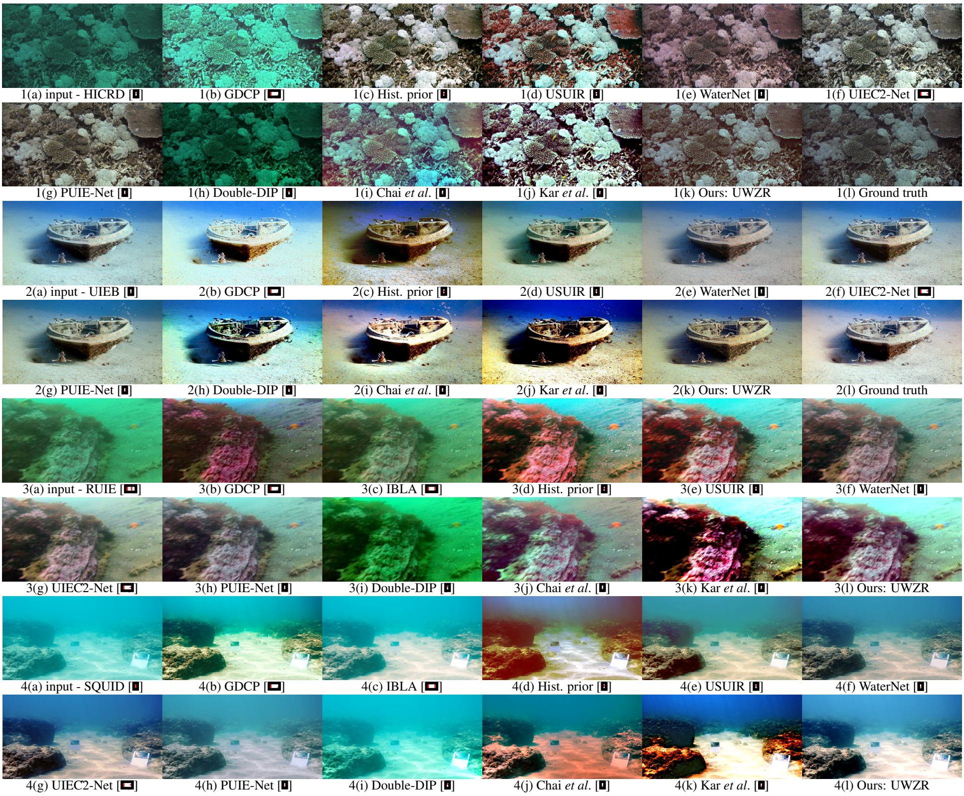

Figure S3: Input UW image (a) from datasets: (1) - HICRD [6], (2) - UIEB [9], (3) - RUIE [10], (4) - SQUID [1] with ground truth (1(l) and 2(l) for HICRD and UIEB) and the restored images from different methods. Note that our results are visually good, and for HICRD and UIEB datasets, our output (1(k) or 2(k)) is close to ground truth (1(l) or 2(l)).

([5], [2], and [7]) are over/under-saturated or have color deviations. Our method performs consistently well on all four datasets.

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