Deep Underwater Image Enhancement

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In an underwater scene, wavelength-dependent light absorption and scattering degrade the visibility of images, causing low contrast and distorted color casts. To address this problem, we propose a convolutional neural network based image enhancement model, i.e., UWCNN, which is trained efficiently using a synthetic underwater image database.

Contributions:

We introduce a novel convolutional neural network model to reconstruct the clear latent underwater image while preserving the original structure and texture by jointly optimizing MSE and SSIM losses. Unlike other mapping function objective minimizing CNN based approaches, our network learns the difference between the degraded underwater image and its clean counterpart.

We incorporate a new underwater image synthesis method that is capable of simulating a diverse set of degraded underwater images for data augmentation. To our best knowledge, it is the first underwater image synthesis method that can simulate different underwater types and degradation levels. Our image synthesis can be used as a guide for subsequent network training and full-reference image quality assessments, which calls for the development of new underwater image enhancement methods.

Our method is a fully data-driven and end-to-end model. It attains the state-of-the-art performance and generalizes well both on synthetic and real-world underwater images with varying color and visibility characteristics. Hence, our method is suitable for practical applications.

Underwater Image Synthesis

The underwater image of light after scattering can be expressed as：

$$\mathbf{U}_\lambda(x) = \mathbf{I}_\lambda(x) \cdot T_\lambda(x) + B_\lambda \cdot \left(1 - T_\lambda(x)\right)$$

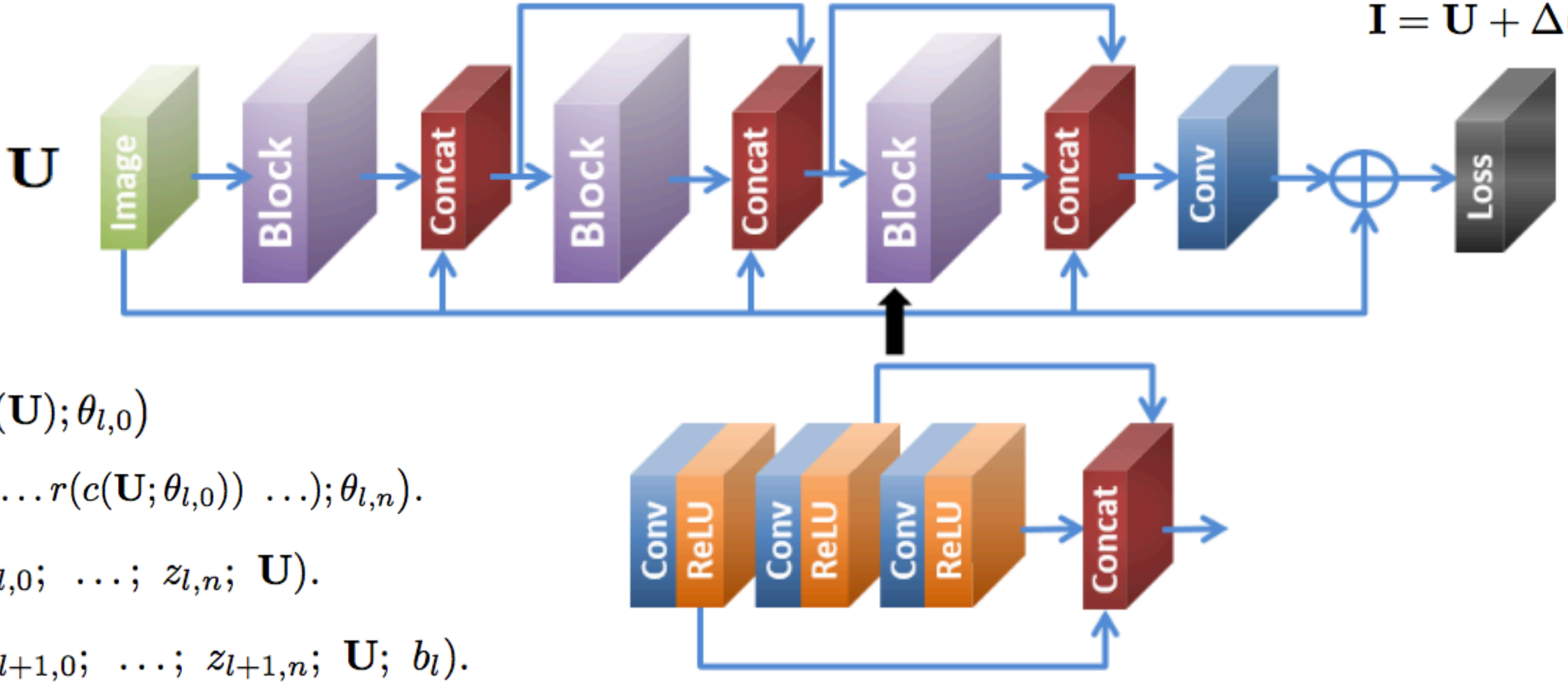
$$T_\lambda(x) = 10^{-\beta_\lambda d(x)}$$

We generate a random homogeneous global atmospheric light $0.8 < B_\lambda < 1$.
Then, we vary the depth d(x) from 0.5m to 15m.

Network Architecture

1.Residuals

$$\mathbf{I} = \mathbf{U} + \Delta(\mathbf{U}, \theta)$$



2.Blocks

$$z_{l,0} = r\big(c(\mathbf{U}); \theta_{l,0}\big)$$

$$z_{l,n} = r\big(c(\ldots r(c(\mathbf{U}; \theta_{l,0}))\ \ldots); \theta_{l,n}\big).$$

$$b_l = h(z_{l,0};\ \ldots;\ z_{l,n};\ \mathbf{U}).$$

$$b_{l+1} = h(z_{l+1,0};\ \ldots;\ z_{l+1,n};\ \mathbf{U};\ b_l).$$

$$\Delta(\mathbf{U}, \theta) = c(b_{l+m}, \theta_{l+m,n}).$$

Fig. 3. Our UWCNN model where "Conv" are the convolutional layers, "Concat" are the stacked convolutional layers, "ReLU" is the rectified linear unit.

Network Loss

MSE loss

$$L_{MSE} = \frac{1}{M}\sum_{i=1}^{M}\left|\left[\mathbf{U}(x_i) + \Delta\Big(\mathbf{U}(x_i), \theta(x_i)\Big)\right] - \mathbf{I}^*(x_i)\right|^2$$

It can well preserve the sharpness of edges and details.

SSIM loss

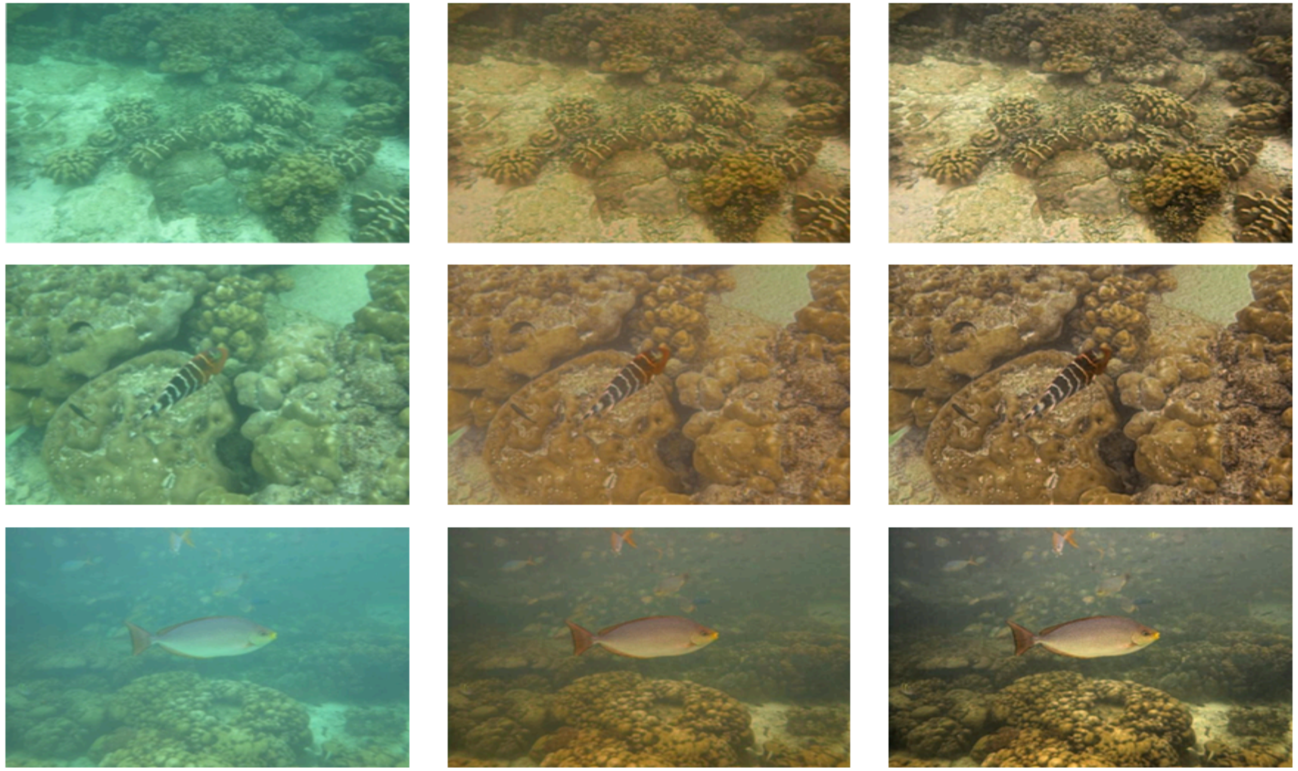
$$L_{SSIM} = 1 - \frac{1}{M}\sum_{i=1}^{M} SSIM(x_i).$$

$$SSIM(x) = \frac{2\mu_{I*}(x)\mu_I(x) + c_1}{\mu_{I*}^2(x) + \mu_I^2(x) + c_1} \cdot \frac{2\sigma_{I*I}(x) + c_2}{\sigma_{I*}^2(x) + \sigma_I^2(x) + c_2}$$

To impose the structure and texture similarity on the latent image.

Post-processing

The image is first transformed to HSI color space. Then, the ranges of its saturation and intensity components in the HSI color space are normalized to[0,1]. After this simple saturation and intensity normalization, we transform the modified result back to RGB color space.



(a) (b) (c)

Fig. 4. Sample results for qualitative assessment. (a) Original real-world underwater images, (b) results of UWCNN, (c) results of UWCNN+. As visible, our methods remove the greenish tone while reconstructing accurate and vivid latent images.


(a) Raws (b) RED (c) UDCP (d) ODM (e) UIBLA (f) UWCNN (g) GT

Fig. 6. Qualitative comparisons for samples from the test dataset. Our network removes the light absorption effects and recovers the original colors without any artifacts. The types of underwater images in the first column from top to bottom are Type-1, Type-3, Type-5, Type-7, Type-9, Type-I, Type-II, and Type-III.

	Types	RAW	RED	UDCP	ODM	UIBLA	UWCNN
MSE	1	2367.3	3489.7	2062.3	2508.6	2812.6	**587.70**
	3	2676.5	4953.2	3380.6	3130.1	3490.1	**747.50**
	5	4851.2	8385.8	6708.9	3488.9	4563.7	**1295.1**
	7	7381.1	9809.8	8591.6	5337.1	6737.9	**2974.1**
	9	9060.6	5952.3	9500.1	10634.0	8433.1	**4121.5**
	I	1449.0	936.9	1020.7	1272.0	1492.2	**209.70**
	II	941.9	851.3	1466.0	1401.9	1141.4	**251.60**
	III	1851.0	2240.0	2337.6	1701.1	1697.8	**456.40**
PSNR	1	15.535	15.596	15.757	16.085	15.079	**21.790**
	3	14.688	12.789	14.474	14.282	13.442	**20.251**
	5	12.142	11.123	10.862	14.123	12.611	**17.517**
	7	10.171	9.991	9.467	12.266	10.753	**14.219**
	9	9.502	11.620	9.317	9.302	10.090	**13.232**
	I	17.356	19.545	18.816	18.095	17.488	**25.927**
	II	20.595	20.791	17.204	17.610	18.064	**24.817**
	III	16.556	16.690	14.924	16.710	17.100	**22.633**
SSIM	1	0.7065	0.7406	0.7629	0.7240	0.6957	**0.8558**
	3	0.5788	0.6639	0.6614	0.6765	0.5765	**0.7951**
	5	0.4219	0.5934	0.4269	0.6441	0.4748	**0.7266**
	7	0.2797	0.5089	0.2628	0.5632	0.3052	**0.6070**
	9	0.1794	0.3192	0.1624	0.4178	0.2202	**0.4920**
	I	0.8621	0.8816	0.8264	0.8172	0.7449	**0.9376**
	II	0.8716	0.8837	0.8387	0.8251	0.8017	**0.9236**
	III	0.7526	0.7911	0.7587	0.7546	0.7655	**0.8795**

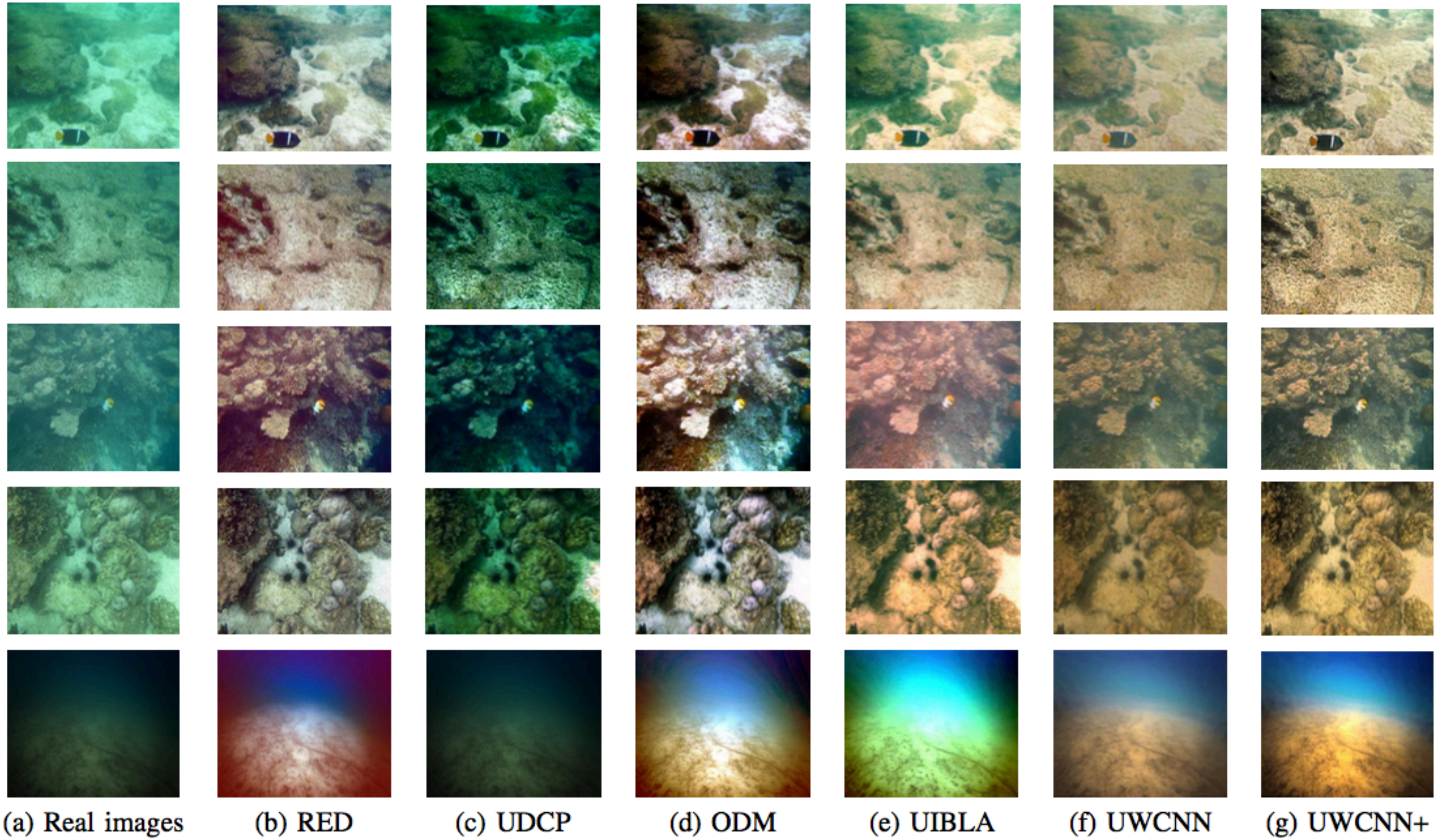
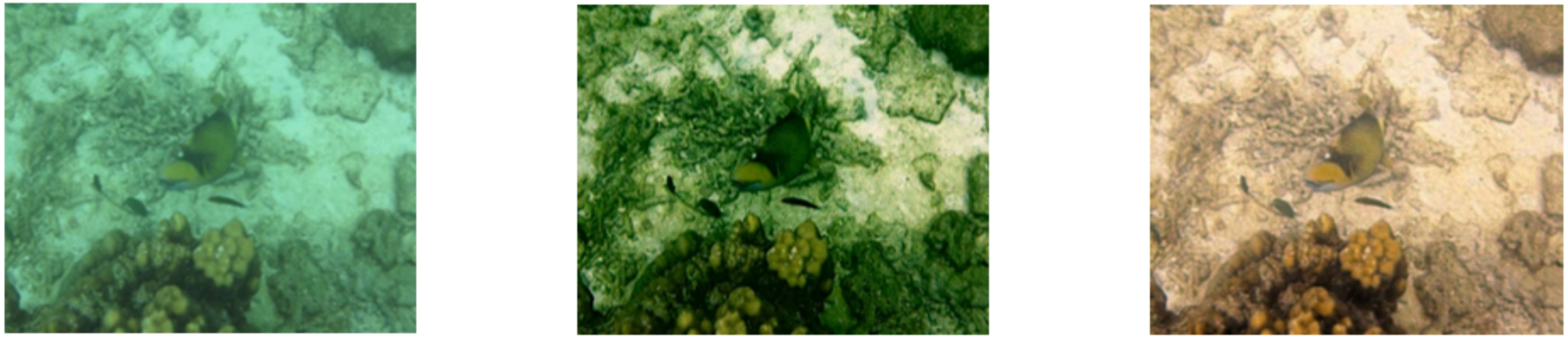


Fig. 7. Results on real-world underwater images taken from the websites. Our method produces results without any visual artifacts, color deviations, and over-saturations. It also unveils spatial motifs and details.

(a) Real image (b) ODM (incorrect reddish tones) (c) UWCNN+

Fig. 8. Comparison with ODM. (a) Real-world image. (b) Result produced by ODM. It blindly introduces wrong colors, in particular, in red gamut. (c) Result produced by UWCNN+.



(a) Real image (b) UIBLA (c) UWCNN+

Fig. 9. Comparison with UIBLA. (a) Real-world image. (b) Result produced by UIBLA, which is a failure case since only greenish tones are enhanced. (c) Result produced by UWCNN+.

Ablation Study

1) UWCNN without residual learning (UWCNN-woRL),
2) UWCNN without dense concatenation (UWCNN-woDC),
3) UWCNN without SSIM loss (UWCNN-woSSIM).

	Types	-woRL	-woDC	-woSSIM	UWCNN
MSE	1	756.96	648.18	**398.77**	587.70
	III	542.68	789.76	**402.92**	456.40
PSNR	1	20.290	20.805	**22.902**	21.790
	III	21.556	20.289	**23.026**	22.633
SSIM	1	0.8450	0.8449	0.8214	**0.8558**
	III	0.8579	0.8359	0.8151	**0.8795**