Underwater Light Field Retention : Neural Rendering for Underwater Imaging

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Paper, code, and dataset are available:
https: //github.com/Ephemeral182/UWNR.

Underwater Image Rendering

Underwater Image Rendering aims to generate a true-to-life underwater image from a given clean one, which could be applied to various practical applications such as underwater image enhancement, camera filter, and virtual gaming. We explore two less-touched but challenging problems in underwater image rendering, namely, **i) how to render diverse underwater scenes by a single neural network? ii) how to adaptively learn the underwater light fields from natural exemplars, i,e., realistic underwater images?** To this end, **we propose a neural rendering method for underwater imaging, dubbed UWNR (Underwater Neural Rendering).** Specifically, UWNR is a data-driven neural network that implicitly learns the natural generated model from authentic underwater images, avoiding introducing erroneous biases by hand-craft imaging models.

Natural Light Field Retention

According to Retinex theory, the image can be disassembled into:

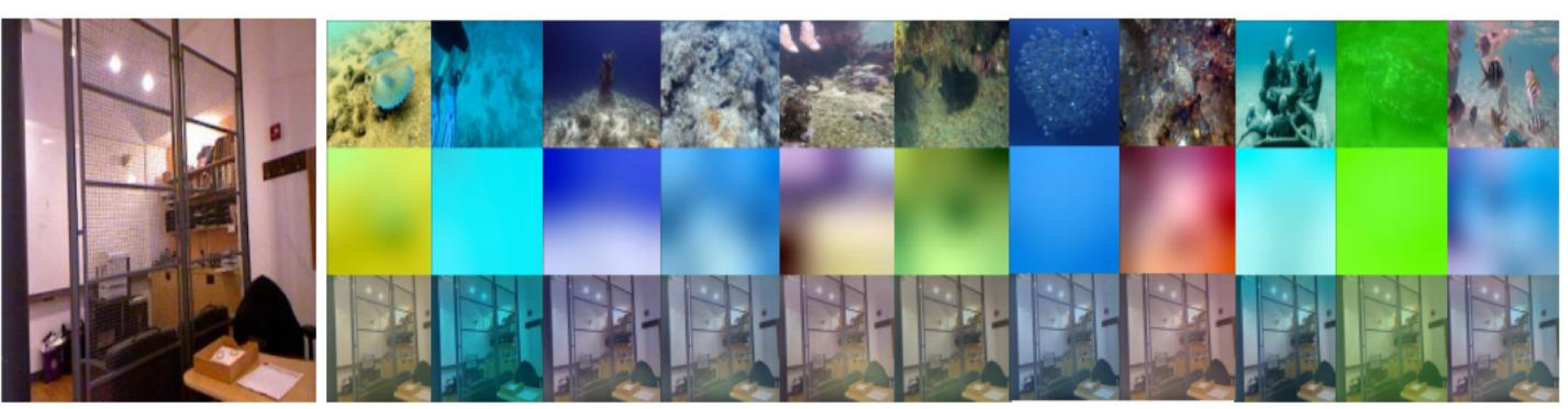
$$x_u = x_l \cdot x_r$$

We perform a multi-scale Gaussian low-pass filter to obtain underwater light field map:

$$x_g = \frac{1}{3}\sum_{\sigma} Gauss_{\sigma}(x_u), \sigma \in \{15,60,90\}$$

We transform it to logarithmic domain and scale it to get the final underwater light field map:

$$x_l = \text{Normalization}(\log x_g)$$

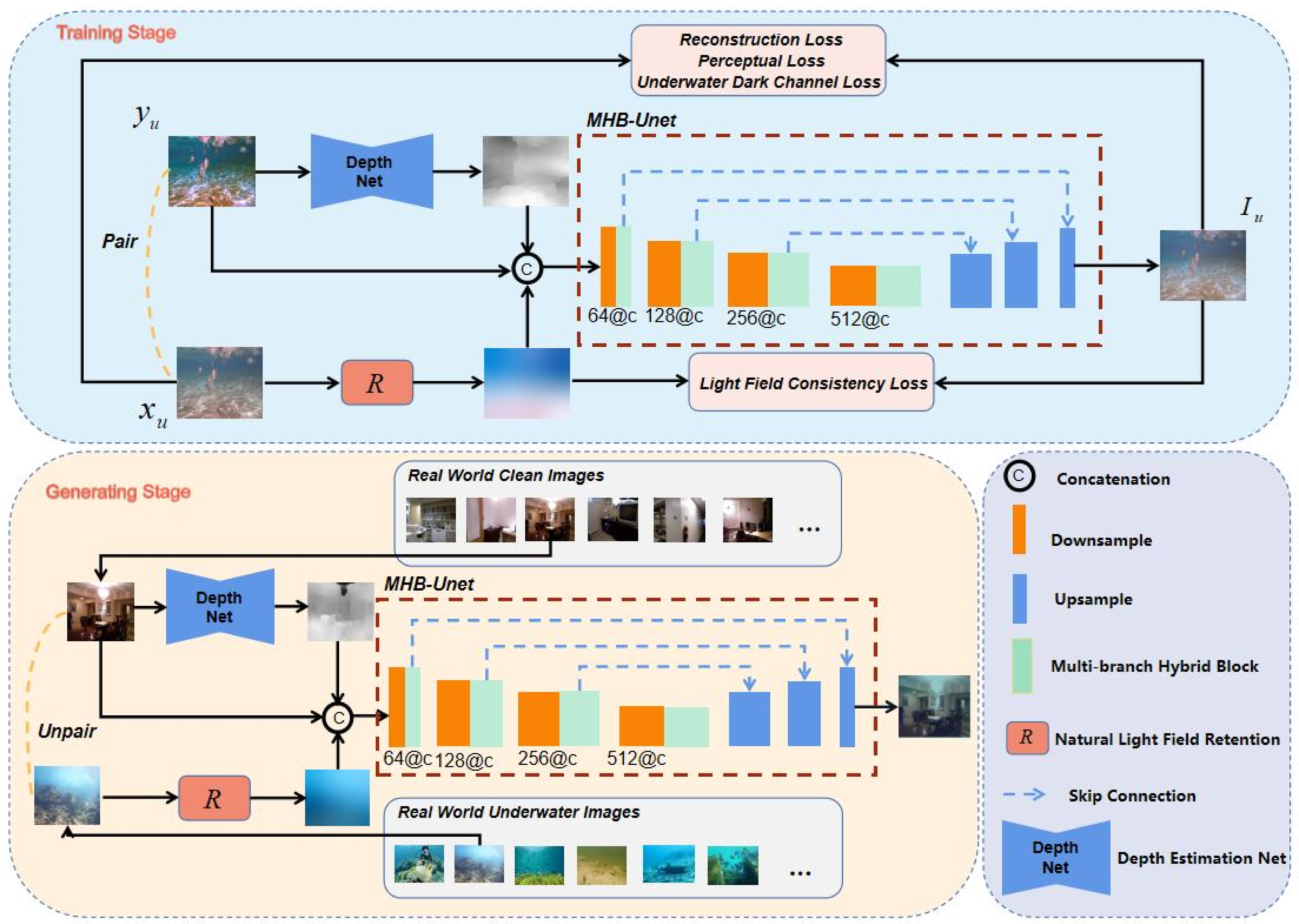


Realistic underwater images (top row), light field maps (middle row), and synthetic underwater images generated by the proposed method (bottom row)

Underwater Image Rendering Framework

- In the training stage, the MHB-Unet is trained to generate the synthetic underwater image with the pair of a real underwater image and its clean ground-truth.

- In the generating stage, a real underwater image can be used to render any unrelated clean image into an underwater image.



Light Field Consistency Loss

$$LF(J) = \frac{1}{3}\sum_{\sigma} Gauss_{\sigma}(J), \sigma \in \{15,60,90\}$$

Underwater Dark Channel Loss

$$UDC(x) = \min_{y \in N(x)}\left[\min_{c \in \{g,b\}} x_i^{\,c}(y)\right]$$

$$L_{udc} = \left\| UDC(I_u) - UDC(x_u) \right\|_1$$

Experiments

Comparative metric analysis of SOTA methods

Metrics	NYU Dataset(890)			SUID Dataset(890)		
	Clean Images	UWGAN [45]	Ours (UWNR)	Clean Images	UISA [18]	Ours(UWNR)
FID	239.36	236.23	**221.93**	274.67	220.90	**216.76**
PSNR	-	18.41	**18.86**	-	12.87	**19.32**
SSIM	-	0.70	**0.77**	-	0.63	**0.77**
UIQM	-	2.28	**2.62**	-	2.44	**2.63**

PSNR, SSIM and UIQM are quantitative results for underwater enhancement of generated images. The underwater enhancement network is Shallow-UWnet (AAAI'21).

Visual comparison with SOTA methods

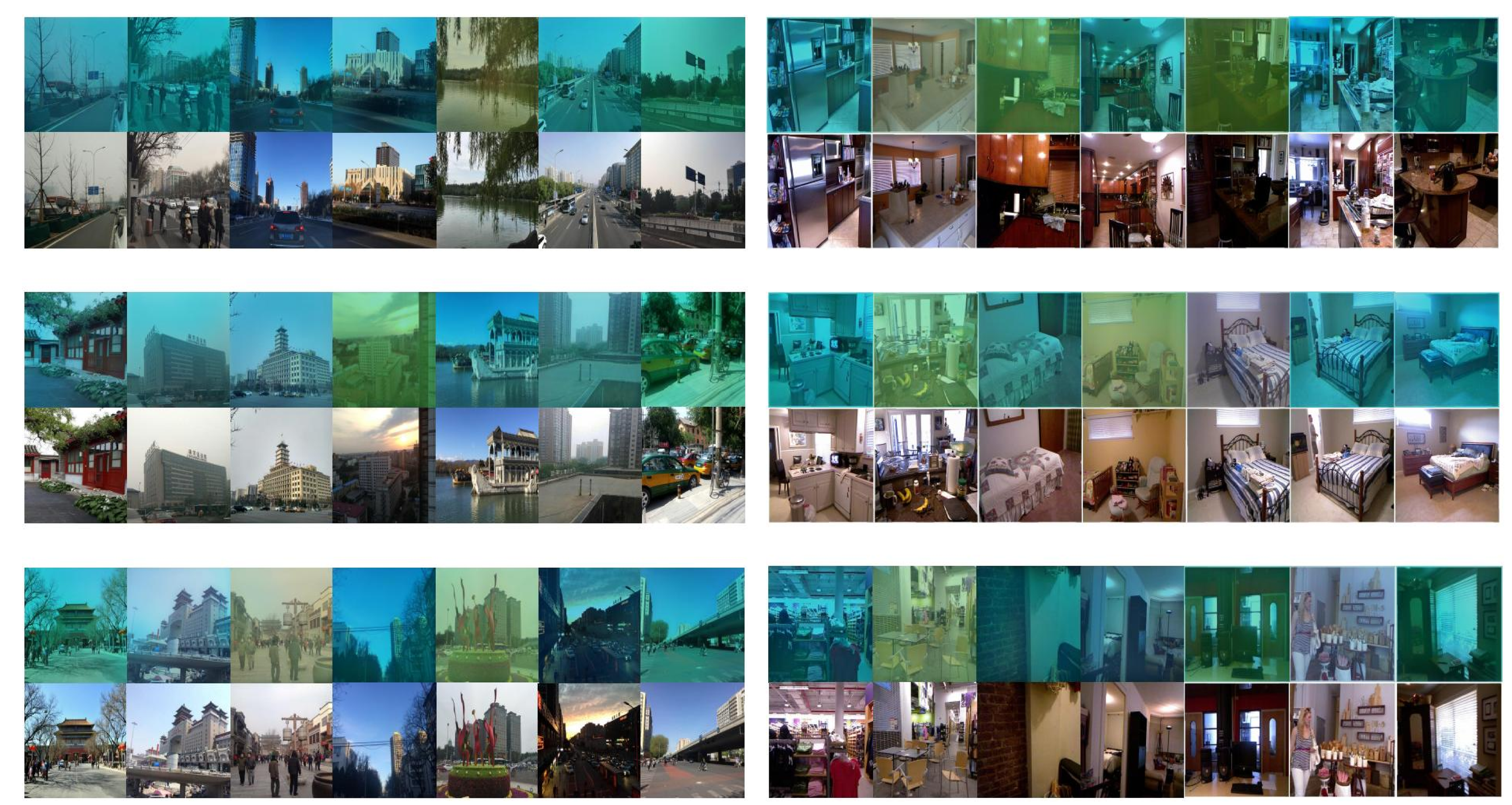
Clean Images

UWGAN

Ours(UWNR)

Real Images

Large Neural Rendering Underwater Dataset



Outdoor **Indoor**