Enhancing Underwater Imagery using Generative Adversarial Networks

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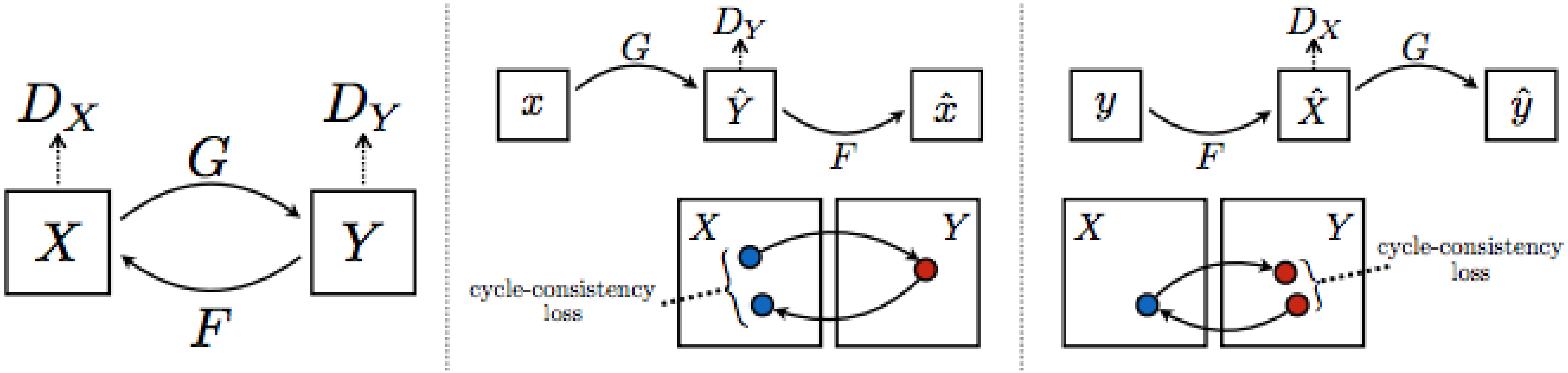
ISSUE

Underwater environments pose unique challenges to visual sensing, as light refraction, absorption and scattering from suspended particles can greatly affect optics.

Often times, these networks require large amounts of data, either labeled or paired with ground truth. However, underwater images distorted by either color or some other phenomenon lack ground truth, which is a major hindrance towards adopting a similar approach for correction.

Methodology

Dataset Generation



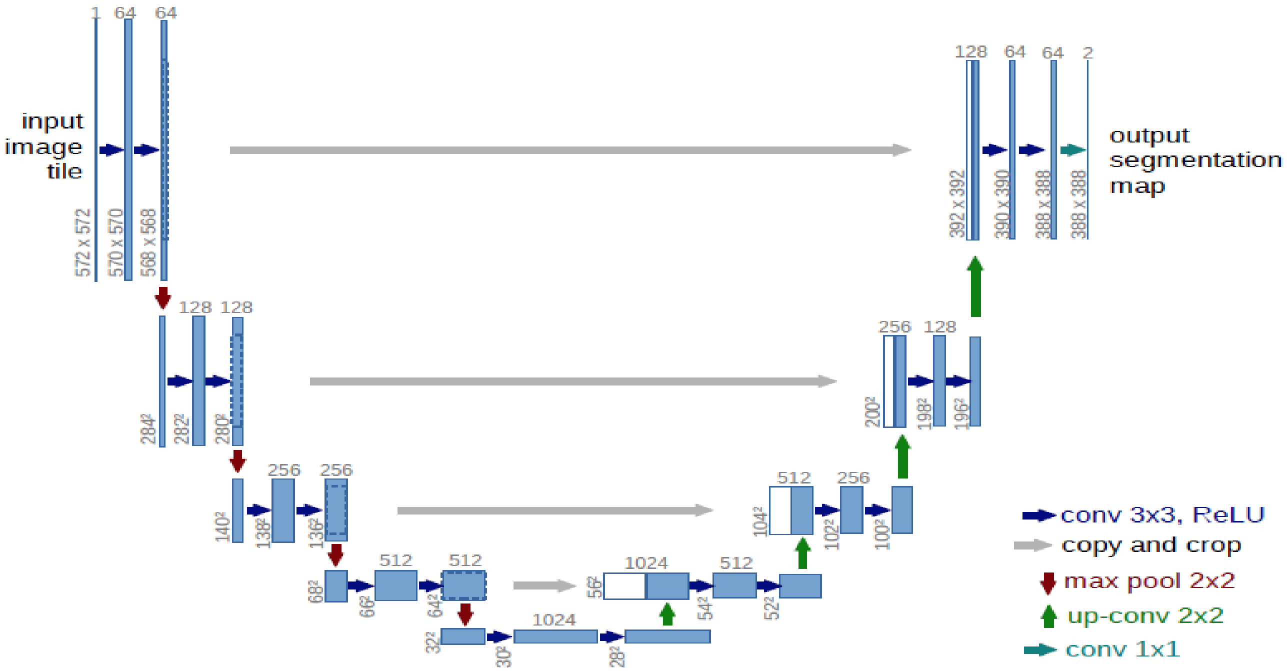
I^C be an underwater image with no distortion

I^D be the same image with distortion

Methodology

Network Architecture

Our generator network is a fully convolutional encoder-decoder, similar to the work of “U-Net”.



Methodology

Loss Function

$$\mathcal{L}^*_{UGAN} = \min_G \max_D \mathcal{L}_{WGAN}(G, D) + \lambda_1 \mathcal{L}_{L1}(G)$$

$$\mathcal{L}_{GDL}(I^C, I^P) = \sum_{i,j} ||I^C_{i,j} - I^C_{i-1,j}| - |I^P_{i,j} - I^P_{i-1,j}||^\alpha + ||I^C_{i,j-1} - I^C_{i,j}| - |I^P_{i,j-1} - I^P_{i,j}||^\alpha$$

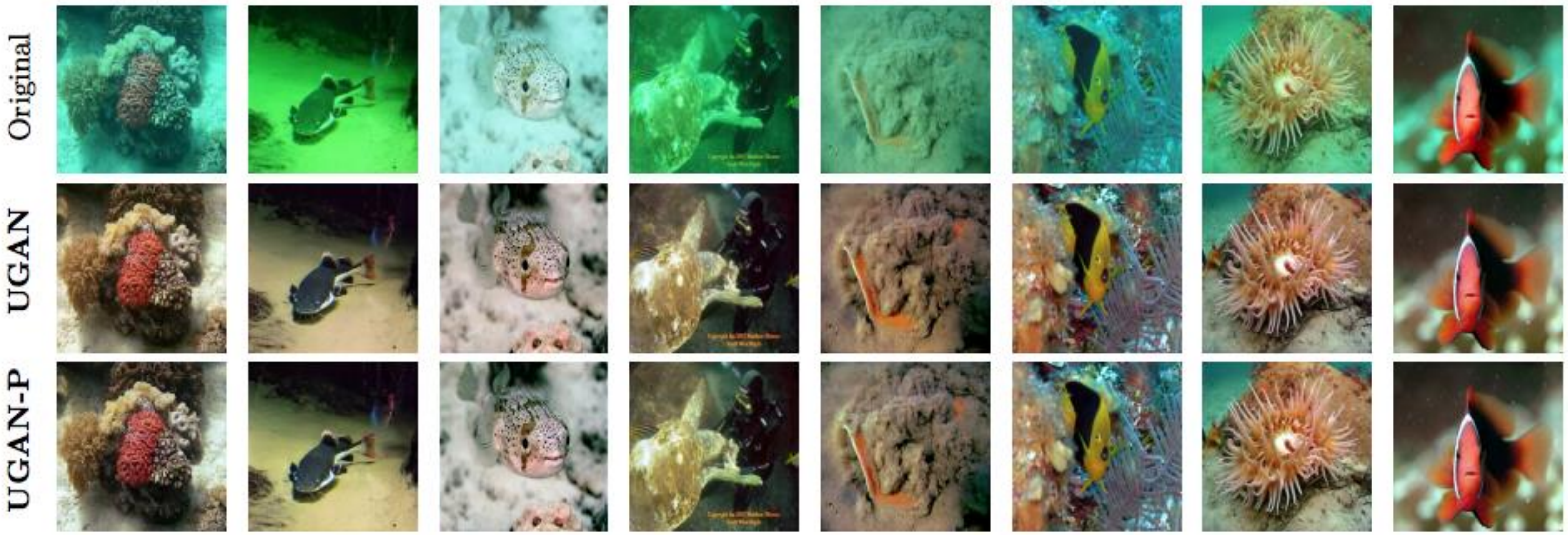
$$\mathcal{L}^*_{UGAN\text{-}P} = \min_G \max_D \mathcal{L}_{WGAN}(G, D) + \lambda_1 \mathcal{L}_{L1}(G) + \lambda_2 \mathcal{L}_{GDL}$$

Experiments

CycleGAN

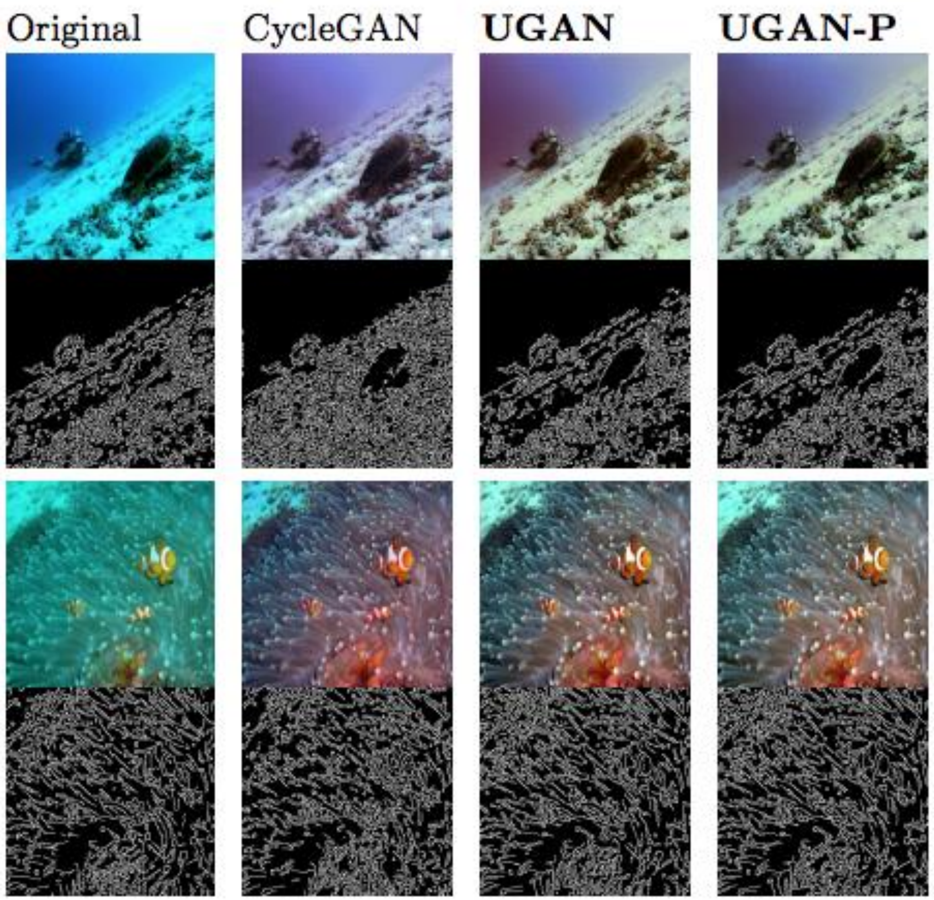
Experiments

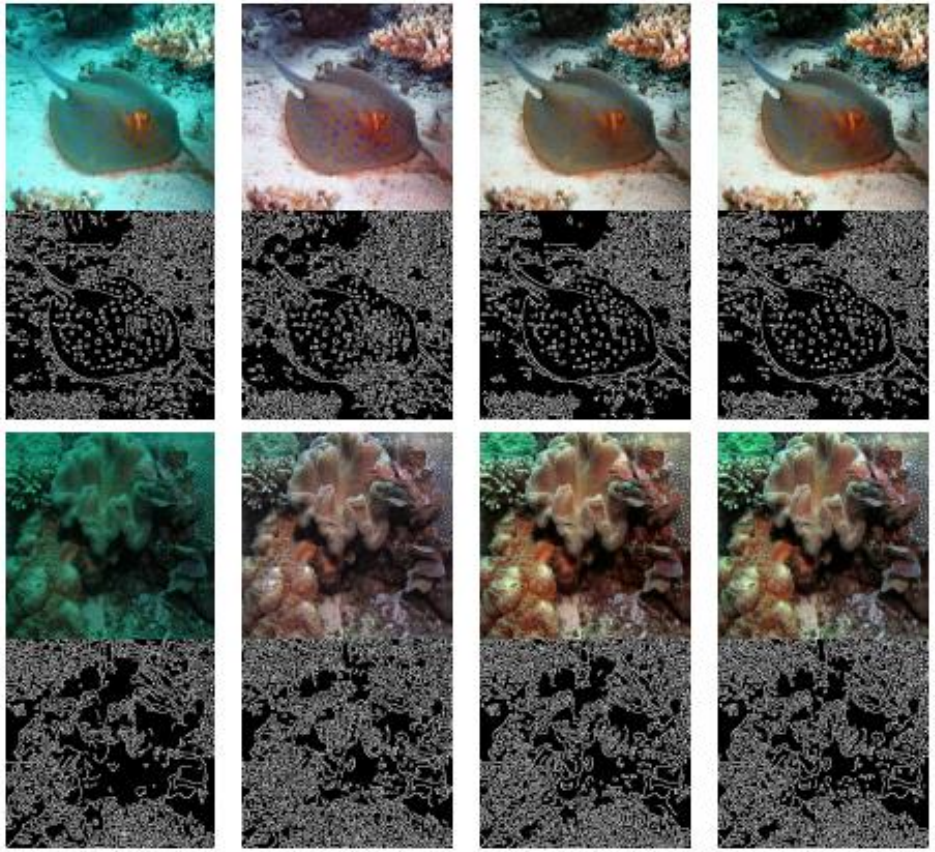
UGAN、UGAN-P



Experiments

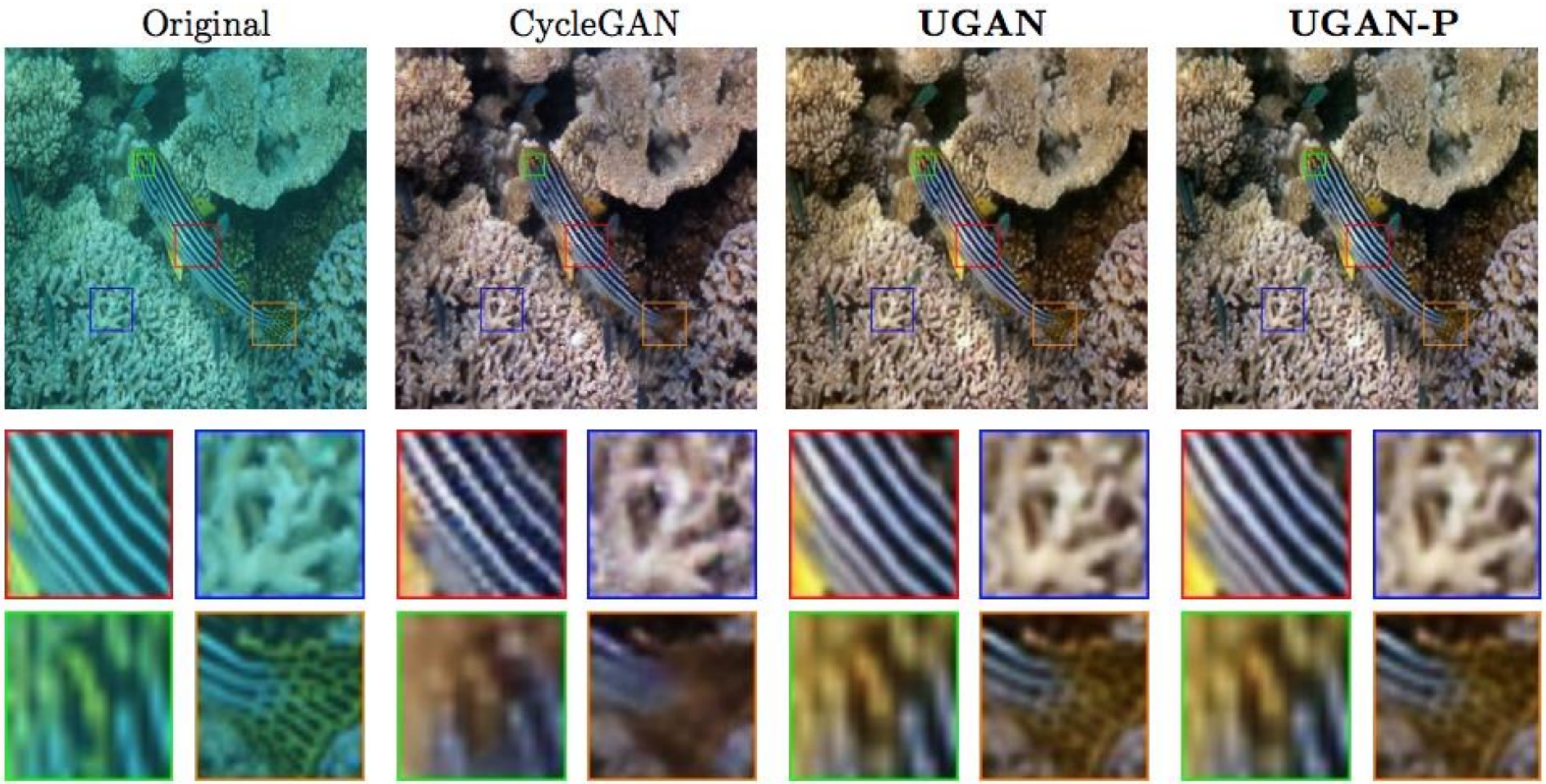
Canny Edge Detector





Experiments

Local image patches



Experiments

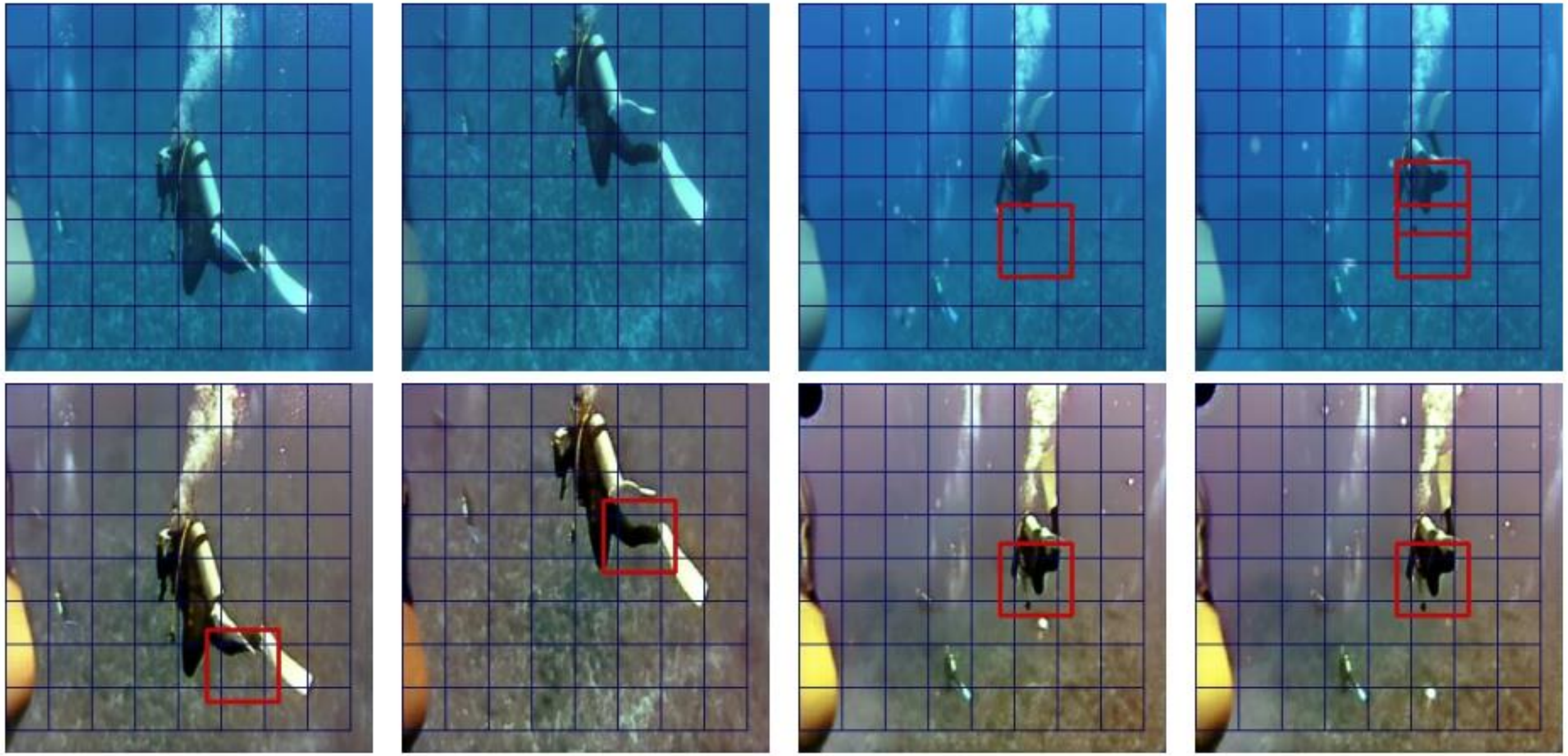
Local image patches

Table 2: Gradient Difference Loss Metrics

Method/Patch	CycleGAN	**UGAN**	**UGAN-P**
Red	11.53	9.39	10.93
Blue	7.52	4.83	5.50
Green	4.15	3.18	3.25
Orange	6.72	5.65	5.79

Experiments

Diver Tracking using Frequency-Domain Detection



Experiments

Diver Tracking using Frequency-Domain Detection

	Correct detection	Wrong detection	Missed detection	Total # of frames
Real	42	14	444	500
Generated	147	24	329	500