Fast Underwater Image Enhancement for Improved Visual Perception

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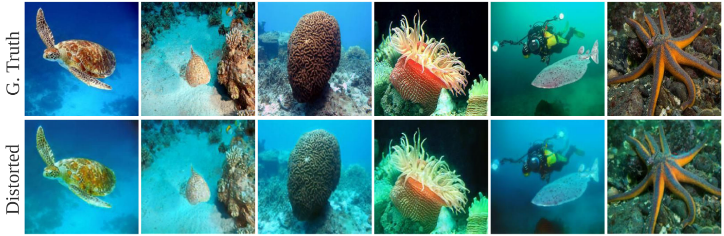
Challenges of underwater imaging

- Light propagation under water is different than in the atmosphere
  - Basically **a different set of non-linear transformations** from real-world scenes to image (color) coordinate system
  - For example, underwater images usually have **higher green or blue hues** because red wavelengths are absorbed in deep water region



Paired instances from EUVP dataset [1]

Challenges of underwater imaging (2)

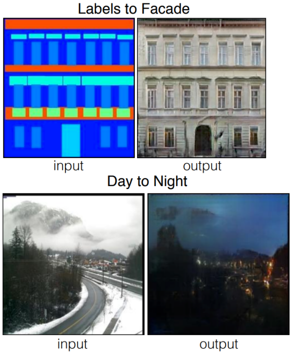
- We can perform **dehazing** and **color correction** using **physical models** with additional parameters, e.g. depth or optical water-quality measures
  - Not always available in robotic applications
  - **Multimodal models are computational expensive for real-time deployment**
- Several models based on **CNN** and **GAN** are proposed
  - Unfortunately, We could not achieve a good performance with deep learning
  - **Underwater data are expensive and difficult to acquire!**

Research overview

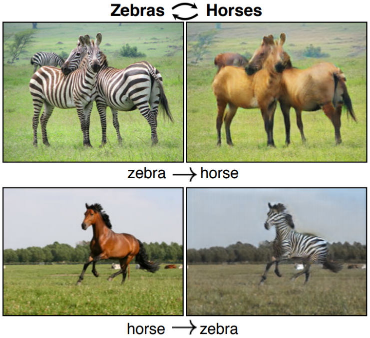
- Published a **EUVP dataset (Enhancement of Underwater Visual Perception)**
  - 12K paired and 8K unpaired underwater of poor and good quality
- Presented a deep learning model for fast underwater image enhancement
  - Framed the problem as **image-to-image translation**
  - Proposed a **conditional GAN architecture** to solve it
  - Evaluated on the proposed dataset

Background: Image-to-image translation

- Transform **style** of images in one domain to another domain
- Some famous examples — **Pix2Pix** [2] and **CycleGan** [3]



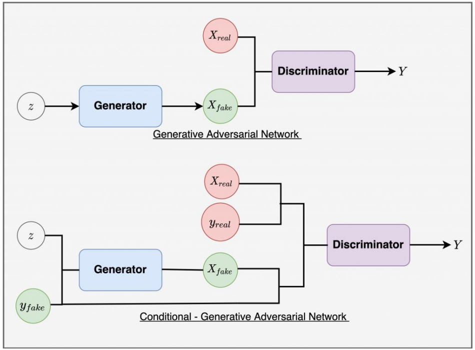
Examples from Pix2Pix [2]



Examples from CycleGAN [3]

Background: Recap of GAN

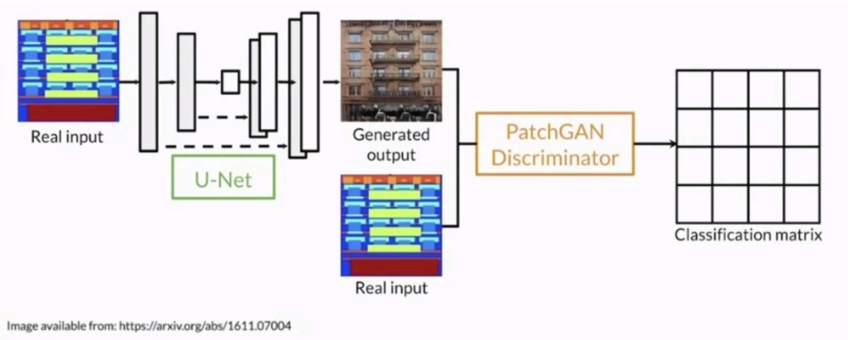
- A two-player min-max game between **generator** and **discriminator**
- **Conditional GANs** impose constrains such that generators produce samples belonged to a specified class



[1] Image available from `https://learnopencv.com/conditional-gan-cgan-in-pytorch-and-tensorflow/`

Background: Pix2Pix in a nutshell

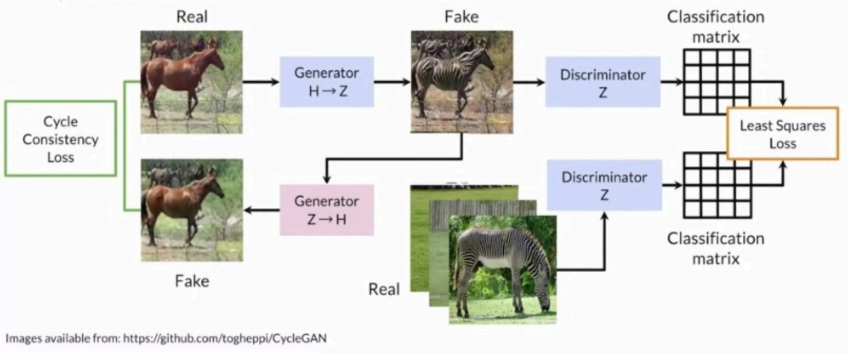
- Generator follows **U-Net architecture**
- Discriminator uses **PatchGAN**, predicting if patches of images are real or fake



[1] Image available from *https://www.haikutechcenter.com/2020/10/pix2pix-gan-architecture-for-image-to.html*

Background: CycleGAN in a nutshell

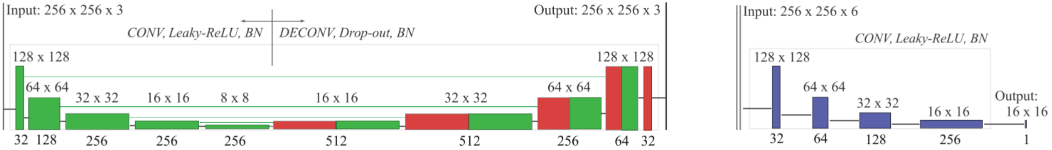
- Although Pix2Pix requires paired training data, we can solve this problem with **cycle-consistency loss**



[1] Image available from *https://www.haikutechcenter.com/2020/11/cyclegan-gan-architecture-for-learning.html*

Methodology: Network Architecture

- Following previous works, generator and discriminator are **mini U-Net** and **PatchGAN**, respectively.



Architecture of FUnIE-GAN [1]

Methodology: Loss Function

- **Paired image translation**
  Let X, Y be the source and target domain. Consider an input Z with a generator G and discriminator D:
  - **Adversarial Loss**

$$L_{cGAN}(G, D) = \mathbb{E}_{X,Y}[\log D(Y)] + \mathbb{E}_{X,Y}[\log(1 - D(X, G(X, Z)))]$$

  - **Global Similarity**

$$L_1(G) = \mathbb{E}_{X,Y,Z}[\|Y - G(X, Z)\|_1]$$

  - **Image content**

$$L_{con}(G) = \mathbb{E}_{X,Y,Z}[\|\Phi(Y) - \Phi(G(X, Z))\|_2]$$

    where Φ denotes the image content function, i.e. the high-level features extracted by a certain layer of a pre-trained **VGG-19 architecture**

Methodology: Loss Function (2)

- **Paired image translation (con't)**

$$G^* = \arg\min_G \max_D L_{cGAN}(G, D) + \lambda_1 L_1(G) + \lambda_c L_{con}(G)$$

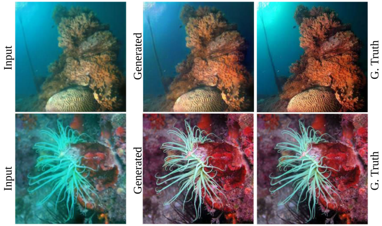
- **Unpaired image translation**
    - Since we do not have access to the ground-truth image, we only use adversarial loss and cycle-consistency loss
    - Let $G_F : \{X, Z\} \rightarrow Y$ and $G_R : \{Y, Z\} \rightarrow X$:

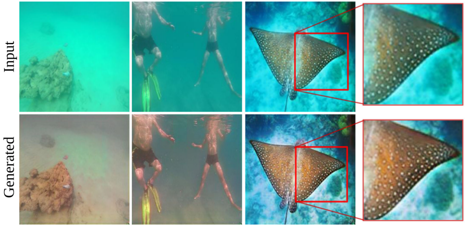
$$G_F^*, G_R^* = \arg\min_{G_F, G_R} \max_{D_Y, D_X} L_{cGAN}(G_F, D_Y) + L_{cGAN}(G_R, D_X) + \lambda_{cyc} L_{cyc}(G_F, G_R)$$

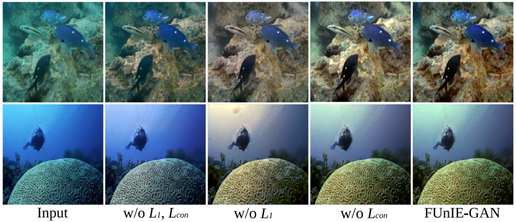
where

$$L_{cyc}(G_F, G_R) = \mathbb{E}_{X,Y,Z}[\|X - G_R(G_F(X, Z))\|_1] + \mathbb{E}_{X,Y,Z}[\|Y - G_F(G_R(X, Z))\|_1]$$

Experiments: Qualitative Analysis







Experiments: Quantitative Analysis

- Three metrics are considered:
  - **Peak Signal-to-Noise Ratio (PSNR)**: measure reconstruction quality

$$PSNR(\mathbf{x}, \mathbf{y}) = 10 \log_{10}\left(255^2 / MSE(\mathbf{x}, \mathbf{y})\right)$$

  - **Structural Similarity (SSIM)**: measure luminance, constrast, and structure

$$SSIM(\mathbf{x}, \mathbf{y}) = \left(\frac{2\mu_{\mathbf{x}}\mu_{\mathbf{y}} + c_1}{\mu_{\mathbf{x}}^2 + \mu_{\mathbf{y}}^2 + c_1}\right)\left(\frac{2\sigma_{\mathbf{xy}} + c_2}{\sigma_{\mathbf{x}}^2 + \sigma_{\mathbf{y}}^2 + c_2}\right)$$

  - **Underwater Image Quality Measure (UIQM)** [4]
    - Quantifies underwater image colorfulness, sharpness, and contrast according to human visual perceptions.

Experiments: Qualitative Analysis and User Study

- **Comparison with other state-of-the-arts**

Model	$PSNR(G(\mathbf{x}), \mathbf{y})$ Input: 17.27 ± 2.88	$SSIM(G(\mathbf{x}), \mathbf{y})$ Input: 0.62 ± 0.075
Uw-HL	18.85 ± 1.76	0.7722 ± 0.066
Mband-EN	12.11 ± 2.55	0.4565 ± 0.097
Res-WGAN	16.46 ± 1.80	0.5762 ± 0.014
Res-GAN	14.75 ± 2.22	0.4685 ± 0.122
LS-GAN	17.83 ± 2.88	0.6725 ± 0.062
Pix2Pix	20.27 ± 2.66	0.7081 ± 0.069
UGAN-P	19.59 ± 2.54	0.6685 ± 0.075
CycleGAN	17.14 ± 2.65	0.6400 ± 0.080
FUnIE-GAN-UP	21.36 ± 2.17	0.8164 ± 0.046
FUnIE-GAN	21.92 ± 1.07	0.8876 ± 0.068

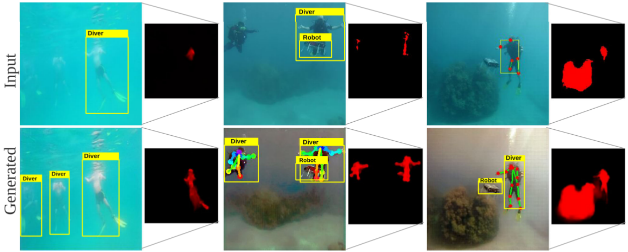
Model	**Paired data** Input: 2.20 ± 0.69 G. Truth: 2.91 ± 0.65	**Unpaired data** Input: 2.29 ± 0.62 G. Truth: N/A
Uw-HL	2.62 ± 0.35	2.75 ± 0.32
Mband-EN	2.28 ± 0.87	2.34 ± 0.45
Res-WGAN	2.55 ± 0.64	2.46 ± 0.67
Res-GAN	2.62 ± 0.89	2.28 ± 0.34
LS-GAN	2.37 ± 0.78	2.59 ± 0.52
Pix2Pix	2.65 ± 0.55	2.76 ± 0.39
UGAN-P	2.72 ± 0.75	2.77 ± 0.34
CycleGAN	2.44 ± 0.71	2.62 ± 0.67
FUnIE-GAN-UP	2.56 ± 0.63	2.81 ± 0.65
FUnIE-GAN	2.78 ± 0.43	2.98 ± 0.51

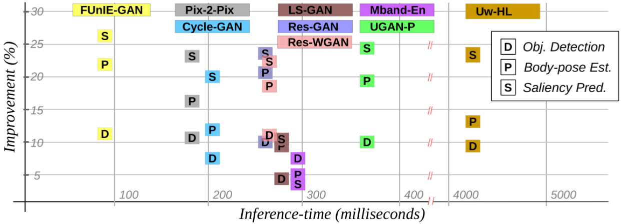
- **Human's preference on generated images**

Model	Rank-1 (%)	Rank-2 (%)	Rank-3 (%)
FUnIE-GAN	24.50	68.50	88.60
FUnIE-GAN-UP	18.67	48.25	76.18
UGAN-P	21.25	65.75	80.50
Pix2Pix	11.88	45.15	72.45

Experiments: Implication

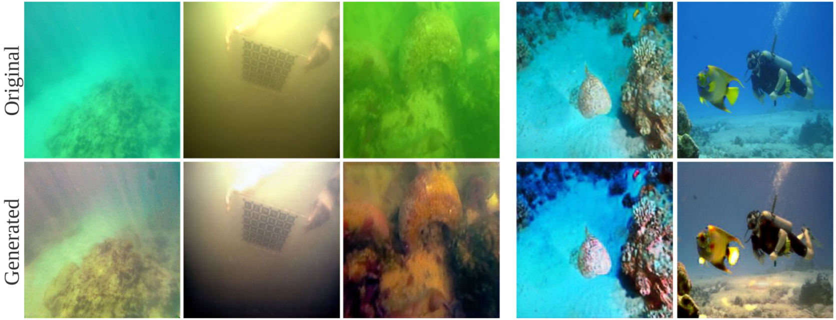
- Improve performance in downstream tasks





Limitations

- Not very effective in severely degraded and texture-less images
- Require careful hyperparameter tuning in unpaired image-to-image translation; otherwise, the discriminator will become too good too early



Issues with extremely low contrast and lack of textures *Inconsistent coloring by unstable training*

References i

[1] M. J. Islam, Y. Xia, and J. Sattar, "Fast underwater image enhancement for improved visual perception," *IEEE Robotics and Automation Letters*, vol. 5, no. 2, pp. 3227–3234, 2020.

[2] P. Isola, J. Zhu, T. Zhou, and A. A. Efros, "Image-to-image translation with conditional adversarial networks," *CoRR*, vol. abs/1611.07004, 2016. [Online]. Available: http://arxiv.org/abs/1611.07004

[3] J. Zhu, T. Park, P. Isola, and A. A. Efros, "Unpaired image-to-image translation using cycle-consistent adversarial networks," *CoRR*, vol. abs/1703.10593, 2017. [Online]. Available: http://arxiv.org/abs/1703.10593

[4] K. Panetta, C. Gao, and S. Agaian, "Human-visual-system-inspired underwater image quality measures," *IEEE Journal of Oceanic Engineering*, vol. 41, no. 3, pp. 541–551, 2016.