Enhancing-Underwater-Imagery-using-Pix2Pix-cGANs

Vidit Agarwal
RoboReG IIT BHU

Abstract

Autonomous underwater vehicles (AUVs) depend on various sensors for decision-making, among which vision-based are an attractive sensing modality. However, the visual data needs to be enhanced as the color red attenuates rapidly and the images become bluish. Minor differences in its altitude to the seafloor also affect the brightness of the images factors such as refraction and absorption, suspended particles in the water, and color distortion resulting in noisy and distorted visual data. This paper proposes a method to enhance the quality of underwater images using Pix2Pix Conditional Generative Adversarial Networks (cGANs) to improve input to vision-driven behaviors. Code Implementation: https://github.com/Viditagarwal7479/Enhancing-Underwater-Imagery-using-Pix2Pix-cGANs

Keywords: Conditional GANs, Pix2Pix cGANs, Underwater Imagery, AUVs.

1. Introduction

Underwater exploration has been steadily growing, and the subfield of use of autonomous robotics is supported by the introduction of novel platforms, sensors, and propulsion mechanisms. While autonomous underwater vehicles are often equipped with various sensors, visual sensing is an attractive option because of its non-intrusive, passive, and energy-efficient nature. Despite the advantages of using underwater imaging, underwater environments pose unique challenges to visual sensing different from standard images, and underwater images suffer from poor visibility due to the attenuation of the propagated light. The light is attenuated exponentially with the distance and depth mainly due to absorption and scattering effects. The random attenuation of the light is the leading cause of the foggy appearance. In contrast, the fraction of the light scattered back from the medium and the sight considerably degrades the scene contrast.

The rest of the paper is structured as follows. Section 2 outlines the works in underwater image enhancement. Section 3 deals with background and theory. Section 4 illustrates the detailed working of the proposed method. Underwater Image Enhancement based on Multiscale Fusion, Section 5 gives results and assessment metrics of the proposed method, and Section 6 deals with the conclusion and summarizes the contributions.

2. Existing Methods

Ke Liu et al. [3] proposed Color channel transfer (CCT) to preprocess the underwater images, light smoothing, and wavelength-dependent attenuation to estimate water light, obtain the attenuation ratio between color channels, and estimate and refine the initial relative transmission of the channel.

Bazeille et al. [7] propose an algorithm to preprocess pictures underwater. Reduce water interference and improve image quality. It is made up of a series of independent processing steps that adjust inconsistent light (homorphic filtering), sound pressure (wavelet denoising), edging edges (anisotropic filtering), and color correction (RGB channels to press bright color). The algorithm is automatic and does not require parameter adjustment.

Sangeetha Mohan et al. [6] proposed work which takes one image as input. A series of functions such as white balancing, gamma correction, sharpening, and manipulation of weight maps are performed on the input image. Finally, a combination of multiscale imagery input was performed to obtain the output effect. In the first stage, the inverted color input is balanced white to produce a color frame, retaining the actual image of the underwater sea. In the second phase, CLAHE is performed on a gamma-modified image. CLAHE plays an essential role in the development of light underwater images. At the same time, histogram measurement was performed on a sharp image. Weight maps analyze imagery features that best define pixel relationships. Finally, the multiscale input pyramid and weight maps were integrated into the final phase.

Cameron Fabbri et al. [1] proposed a UGAN-based approach to enhance underwater images. Their fundamental approach to using a General Adversarial Network in the conditional setting is to learn the representation of unclear underwater images to their clear enhanced version.

Figure 2. Paired samples of ground truth and distorted images. The first row consists of ground truth that we want, and the second row consists of visual data as seen underwater.

3. Methodology

We propose the use of Pix2Pix GANs[2] to enhance underwater images. A Conditional Adversarial Network performs image-to-image translation by translating an image from any arbitrary domain X to another arbitrary domain Y. By letting X be a set of distorted underwater images and Y be a set of undistorted underwater images. By training Pix2Pix GAN on such a dataset, we can generate an image that is the enhanced version of the given unclear underwater image.

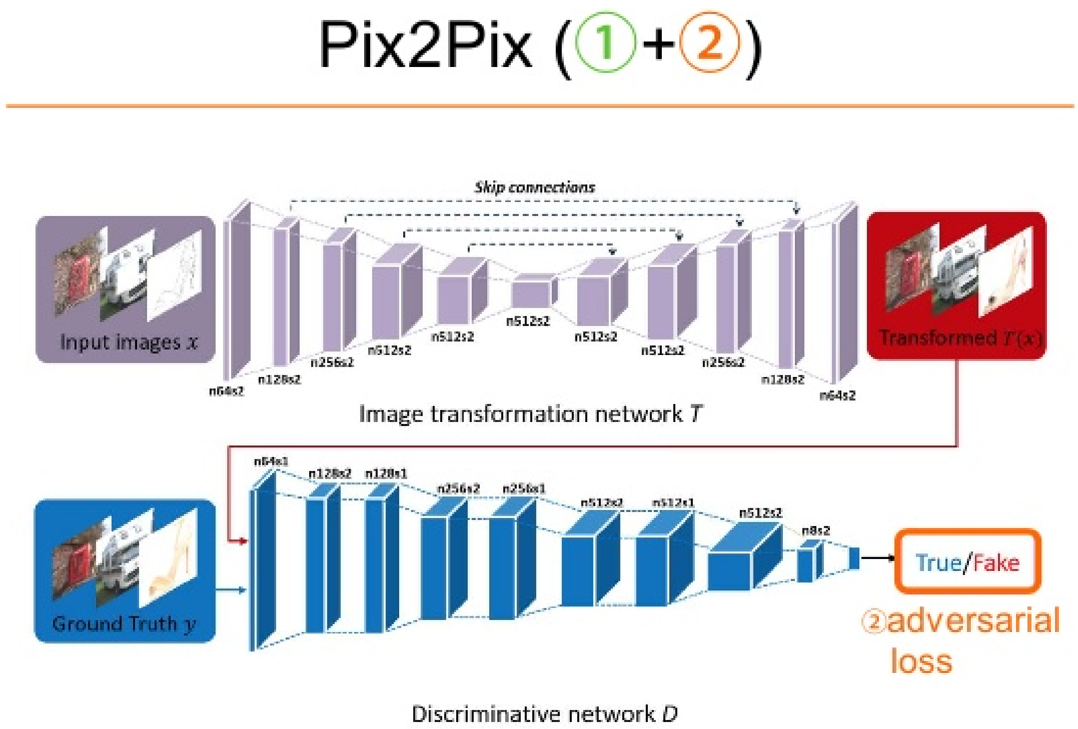


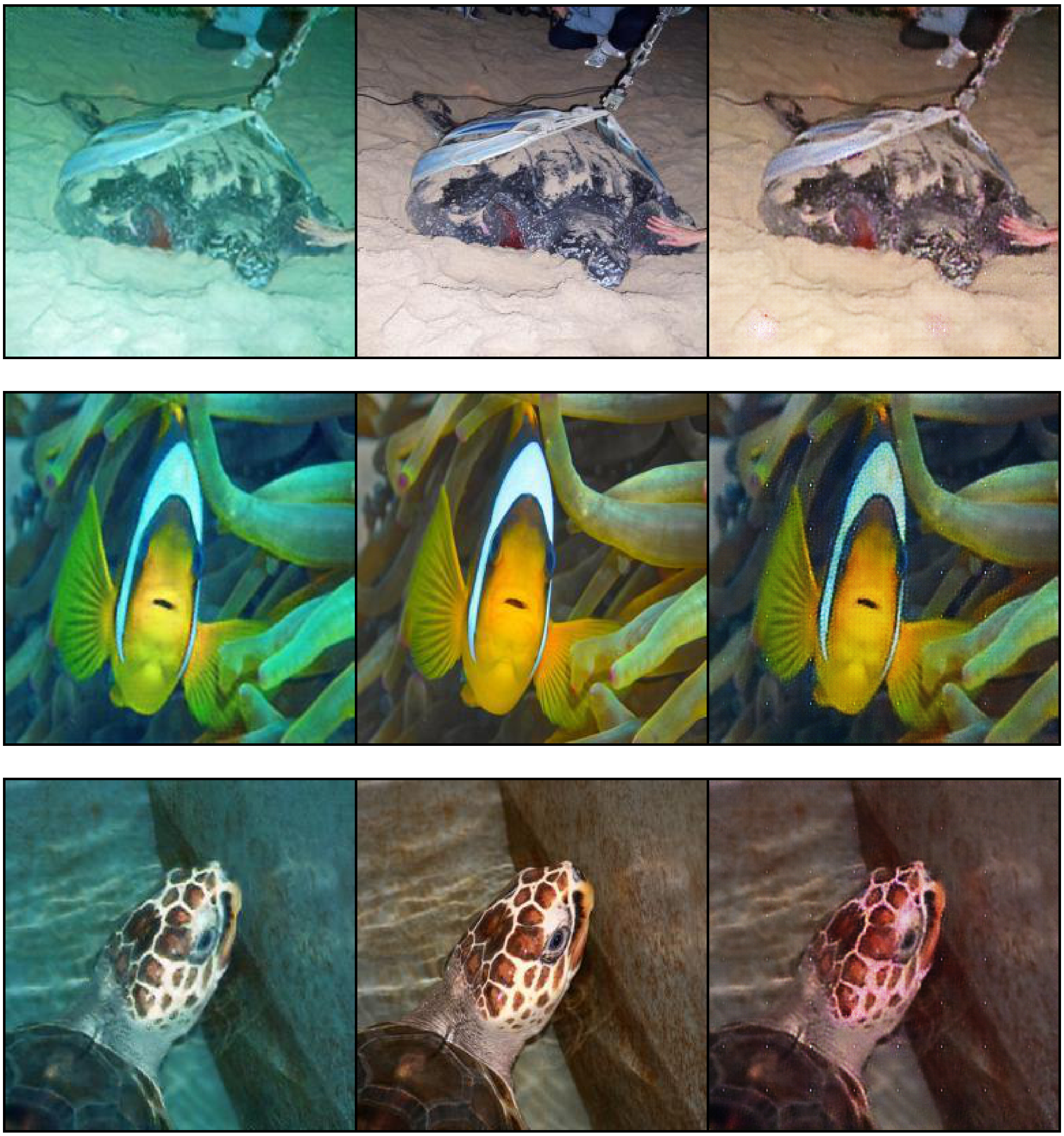
Figure3. Pix2Pix GAN architecture.

4. Dataset Used

The dataset proposed in the paper Enhancing Underwater Imagery Using Generative Adversarial Networks [1] was used in which subsets of ImageNet, which contained underwater images, were selected for the training of a CycleGAN and were manually separated into two classes based on visual inspection. Let X be the set of underwater images with no distortion, and Y be the set of underwater images with distortion. X contained 6143 images, and Y contained 1817 images. The CycleGAN was trained to learn the mapping F: X → Y. Images from X appeared to have come from Y . Finally, our image pairs for training data were generated by distorting all images in X with F . Figure 2 shows sample training pairs.

5. Results

1st column: Underwater Image / 2nd column: Ground Truth / 3rd column: Generated Image



The results are made by training Pix2Pix cGAN over 200 epochs using data parallelism over 4 GEFORCE GTX 1080 Ti.

The pretrained weights can be downloaded from here https://mega.nz/file/uiwjDS5b#OJ2sezjr_-Q4zm5qkF2JBOHZQCGZ63ljBV-xFfd0-Xk.

6. Conclusion

This paper suggests that using pix2pix GANs is a promising approach for enhancing underwater color images. Quantitative and qualitative results demonstrate the effectiveness of this method, and using the corrected images from the approach mentioned above will yield better results than uncorrected image sequences in the fields where underwater imaging is used.

References

[1] Cameron Fabbri, Md Jahidul Islam, and Junaed Satta. Enhancing Underwater Imagery using Generative Adversarial Networks. In IEEE International Conference on Robotics and Automation (ICRA), 2018 https://ieeexplore.ieee.org/document/8460552

[2] Phillip Isola, Jun-Yan Zhu, Tinghui Zhou, and Alexei A. Efros. Image-to-Image Translation with Conditional Adversarial Networks. In CVPR, 2017. https://arxiv.org/abs/1611.07004

[3] Ke Liu and Yongquan Liang, "Underwater image enhancement method based on adaptive attenuation-curve prior," Opt. Express 29, 10321-10345 (2021)

[4] Schettini, R., Corchs, S. Underwater Image Processing: State of the Art of Restoration and Image Enhancement Methods. EURASIP J. Adv. Signal Process. 2010, 746052 (2010). https://doi.org/10.1155/2010/746052

[5] C. Ancuti, C. O. Ancuti, T. Haber and P. Bekaert, "Enhancing underwater images and videos by fusion," 2012 IEEE Conference on Computer Vision and Pattern Recognition, 2012, pp. 81-88, doi: 10.1109/CVPR.2012.6247661.

[6] Sangeetha Mohan, Philomina Simon, Underwater Image Enhancement based on Histogram Manipulation and Multiscale Fusion, Procedia Computer Science,Volume 171,2020,Pages 941-950,ISSN 1877-0509, https://doi.org/10.1016/j.procs.2020.04.102, https://www.sciencedirect.com/science/article/pii/S1877050920310784

[7] Bazeille S, Quidu I, Jaulin L, Malkasse JP: Automatic underwater image pre-processing. Proceedings of the Caracterisation du Milieu Marin (CMM '06), 2006