UGAN: Underwater Image Restoration using Generative Adversarial Networks

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Abstract—Autonomous underwater robots often rely on visual input for decision making due to its non-intrusive and passive nature . However, due to many factors such as light refraction, particles in the water, and color distortion, images are often times very noisy. This paper propose a method using Generative Adversarial Networks (GANs) to denoise underwater images, and show that these images provide both increased accuracy for an underwater tracking algorithm, as well as a more visually appealing image. Furthermore, we show how recently proposed methods are able to generate a dataset for the purpose of underwater image reconstruction.

I. INTRODUCTION

Vision is a commonly used sensor in autonomous underwater robots due to its non-intrusive, passive, and energy effecient nature. The monitoring of coral reefs [1], deep ocean exploration [2], and mapping of the seabed are all tasks suitable for autonomous robots because they provide safety by taking the risk instead of a human. Despite the advantages vision provides, many underwater environments can be quite noisy due to light refraction and particles present in the water. Because red wavelengths are quickly absorbed by water, images tend to have a green or blue hue to them. As you go deeper, this worsens as more and more red wavelengths are being absorbed. This extremely non-linear distortion has many factors such as the amount of light present (overcast vs sunny or depth), particles in the water, time of day, and the camera being used. This may cause difficulty in tasks such as segmentation, tracking, or classification due to their indirect or direct use of color.

As color and illumination begin to change with the depth, vision based algorithms must be very generalizable in order to work within the depth ranges a robot may operate in. Because of the high cost and difficulty of acquiring a variety of underwater data, as well as the high amount of noise introduced, many algorithms may perform poorly in these different domains. Figure 1 shows the high variability that may occur in underwater vision. A step towards a solution to this issue is to be able to restore the images such that they appear to be above water, i.e., with colors corrected and particles removed. By performing a many to one mapping of these domains from underwater to not underwater (what the image would look like in the air), algorithms that have
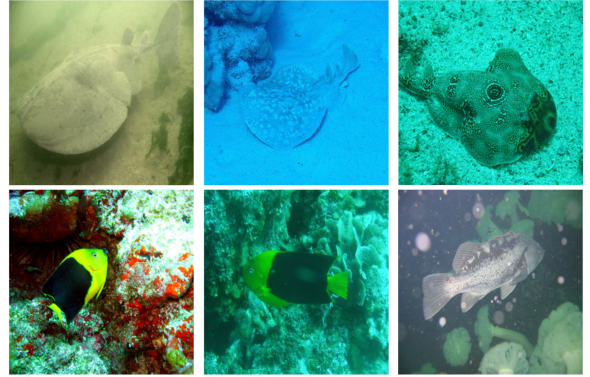

Fig. 1. Underwater images showing the vast divesity of noise that can occur, including different hues of green and blue, as well as particles in the water.

difficulty performing across multiple forms of noise may be able to focus only one clean domain.

Deep neural networks have been shown to be powerful non-linear function approximators, especially in the field of vision. Often times, these networks recquire large amounts of data, either labeled or paired with ground truth. For the problem of automatically colorizing grayscale images, paired training data is essentially free due to the fact that any color image can be converted to black and white. However, underwater images distorted by either color or some other visual effect lack ground truth. We use the recently proposed CycleGAN [3], which learns to translate an image from domain X to domain Y, as a way to generate a paired dataset. By letting X be a set of undistorted underwater images, and Y be a set of distorted underwater images, we can generate an image that appears to be underwater while retaining ground truth.

II. RELATED WORK

While there have been many very successful recent approaches towards colorization [4], [5], all are focused on the task of grayscale to color. Color correction and image restoration for the underwater domain has been less explored. The work of [6] used an energy minimization formulation using a Markov Random Field.

III. Method

Recent work in generative models, specifically Generative Adversarial Networks (GANs), have shown great success in areas such as inpainting [7], style transfer [8], and image-to-image translation [9], [3]. This is highly due to their ability to provide a more meaningful loss than simply the Euclidean distance, which has been shown to produce blurry results.

A. Generative Adversarial Networks

B. Objective

C. Network Architectures

1) Generator:

2) Discriminator:

IV. Conclusion

Acknowledgment

References

[1] F. Shkurti, A. Xu, M. Meghjani, J. C. G. Higuera, Y. Girdhar, P. Giguere, B. B. Dey, J. Li, A. Kalmbach, C. Prahacs, *et al.*, "Multi-domain monitoring of marine environments using a heterogeneous robot team," in *Intelligent Robots and Systems (IROS), 2012 IEEE/RSJ International Conference on*, pp. 1747–1753, IEEE, 2012.

[2] L. Whitcomb, D. R. Yoerger, H. Singh, and J. Howland, "Advances in underwater robot vehicles for deep ocean exploration: Navigation, control, and survey operations," in *Robotics Research*, pp. 439–448, Springer, 2000.

[3] J.-Y. Zhu, T. Park, P. Isola, and A. A. Efros, "Unpaired image-to-image translation using cycle-consistent adversarial networks," *arXiv preprint arXiv:1703.10593*, 2017.

[4] R. Zhang, P. Isola, and A. A. Efros, "Colorful image colorization," in *European Conference on Computer Vision*, pp. 649–666, Springer, 2016.

[5] S. Iizuka, E. Simo-Serra, and H. Ishikawa, "Let there be color!: joint end-to-end learning of global and local image priors for automatic image colorization with simultaneous classification," *ACM Transactions on Graphics (TOG)*, vol. 35, no. 4, p. 110, 2016.

[6] L. A. Torres-Méndez and G. Dudek, "Color correction of underwater images for aquatic robot inspection," in *EMMCVPR*, pp. 60–73, Springer, 2005.

[7] D. Pathak, P. Krahenbuhl, J. Donahue, T. Darrell, and A. A. Efros, "Context encoders: Feature learning by inpainting," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 2536–2544, 2016.

[8] L. A. Gatys, A. S. Ecker, and M. Bethge, "Image style transfer using convolutional neural networks," in *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2016.

[9] P. Isola, J.-Y. Zhu, T. Zhou, and A. A. Efros, "Image-to-image translation with conditional adversarial networks," *arXiv preprint arXiv:1611.07004*, 2016.