Detecting Waterborne Debris with Sim2Real and Randomization

Jie Fu [*1 2] **Ritchie Ng** [*3] **Mirgahney Mohamed** [4] **Yi Tay** [5] **Kris Sankaran** [1] **Shangbang Long** [6]
Alfredo Canziani [7] **Chris Pal** [1 2] **Moustapha Cisse** [8]

Abstract

This document provides a basic paper template and submission guidelines. Abstracts must be a single paragraph, ideally between 4–6 sentences long. Gross violations will trigger corrections at the camera-ready phase.

1. Introduction

Marine debris pollution is one of the most ubiquitous and pressing environmental issues affecting our oceans today. Clean up efforts, such as the Great Pacific Garbage Patch project (Cleanup, 2019), have been implemented across the planet with the goal of combating this problem. However, human resources to accomplish this goal are limited and the afflicted area is vast. To this end, unmanned vehicles that are capable of automatically detecting and removing small-sized debris would be a great complementary approach to existing large-scale garbage collectors. Due to the complexity of fully functioning unmanned vehicles for both detecting and removing debris, in this project we focus on the detection task as a first step.

From the perspective of machine learning, there is an unfortunate lack of sufficient labeled data for training a specialized detector, e.g., a classifier which can distinguish debris from other objects like wild animals. Moreover, pre-trained detectors on other domains would be ineffective while creating such datasets manually would be very costly.

Due to recent progresses of training deep models with synthetic data (Tremblay et al., 2018; Beery et al., 2019) and domain randomization (Tobin et al., 2017; Luo et al., 2018), we propose to train a debris detector based on a mixture of real and synthetic images. The synthetic images are rendered by Unreal Engine 4 (Qiu & Yuille, 2016), and they are further augmented by domain randomization (Tobin et al., 2017; Luo et al., 2018). After training, we deploy the detector in the wild.

Through this project, we aim to show that game-based simulations are viable options for data augmentation and may benefit many low-resource settings which are common in real-world environmental protection applications. Specifically pertaining to the problem at hand, the social impact of a successfully and automatically deployed garbage cleaner would be a big win for protecting the environment.

We also notice that most existing debris detection online services keep the annotated data and trained models private. Therefore, we will open-source the dataset, its generator, model implementations and the whole pipeline for encouraging follow-up research in this direction.

2. Methodology

The real-world training data is from (Thung & Yang, 2016) and COCO (Lin et al., 2014), which contains 2527 images for different trash. We then mix this dataset with synthetic images generated by a game engine which is further augmented by randomization.

We use a YOLOv3 object detector (Redmon & Farhadi, 2018) pre-trained on COCO dataset (Lin et al., 2014) and a small-scale trash dataset (Thung & Yang, 2016). This object detector is then fine-tuned on an augmented dataset consisting of real images and synthetic ones. For example, we can render a plastic bottle in a lake using Unreal Engine 4 (Qiu & Yuille, 2016), and then use domain randomization (e.g. replace the original background with random textures) (Tobin et al., 2017; Luo et al., 2018) to augment the dataset.

We expect the proposed pipeline to be able to recognize waterborne debris (e.g. plastic bottles) with different appearances in the wild more robustly compared to those only trained on real-world images.

3. Evaluation

As an initial experiment, we focus on the detection of plastics, as it contributes the most to ocean debris. We first train our plastics detector on the mixture of real and synthetic images, and then test its effectiveness in the wild. Specifically,

[*]Equal contribution [1]Mila [2]Polytechnic Montréal [3]National University of Singapore [4]The African Institute for Mathematical Sciences [5]Nanyang Technological University [6]Peking University [7]New York University [8]Google AI. Correspondence to: Jie Fu <jie.fu@polymtl.ca>, Ritchie Ng <ritchieng@u.nus.edu>.

Appearing at the International Conference on Machine Learning AI for Social Good Workshop, Long Beach, United States, 2019.

we will load our detector into a drone and use it to search for plastics in several lakes or rivers.

4. Preliminary Experiments

At this point, we have generated over 1000 unique synthetic ocean debris images comprising more than 100 different objects with their respective segmentation masks. Given our custom debris world created through Unreal Engine 4 we are able to capture images comprising unlimited variations of angles, distance to objects, types of objects and distribution of objects. Alongside the images captured, we are able to automatically generate segmentation masks as the game engine has the ground truth. This has an advantage over real images where manual labelling is required. Samples of the synthetic images and their respective segmentation masks can be seen in Figure 1.

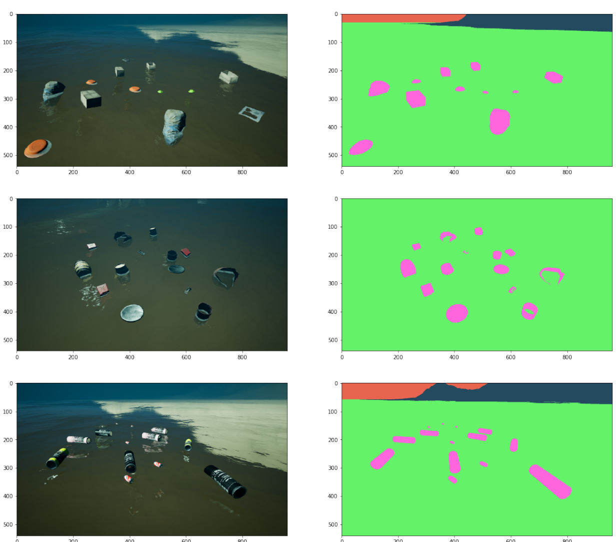

Figure 1. Images on the left are generated by our custom debris world, and images on the left are automatically generated segmentation masks.

Given one unique image taken from the game engine, we can generate unlimited unique samples with domain randomization applied. A sample can be seen in Figure 2 that shows a synthetic ocean debris image generated through Unreal Engine 4, the respective segmentation mask and 6 samples that have undergone domain randomization.

5. Discussion

At this stage, game engines do not provide sufficient amount of ocean animal models, thus deploying the unmanned vehicles might hurt animals. Since synthetic examples can improve generalization for rare animal classes (Beery et al., 2019), we would consider incorporating this component before deployment.

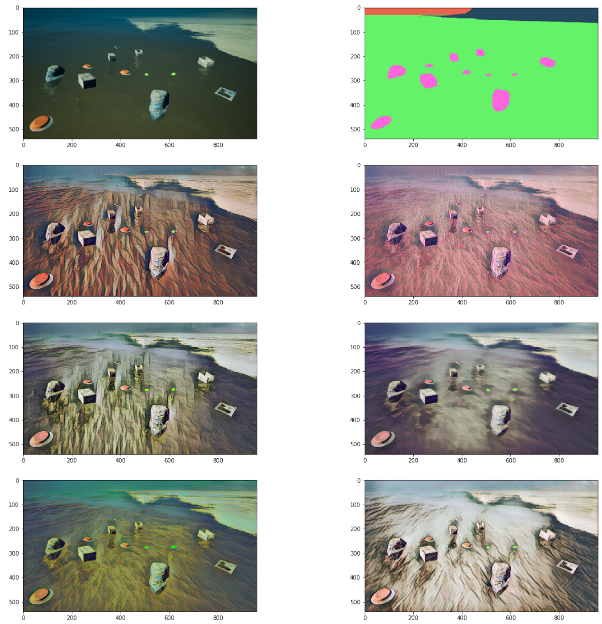

Figure 2. The top left image is the synthetic image of debris in the sea. The top right image is the segmentation mask. The remaining 6 images are domain randomization permutations generated from the original synthetic image.

Acknowledgements

We would like to thank NVIDIA for $10,000 donation.

References

Beery, S., Liu, Y., Morris, D., Piavis, J., Kapoor, A., Meister, M., and Perona, P. Synthetic examples improve generalization for rare classes, 2019.

Cleanup, O. The ocean cleanup, May 2019. URL https://www.theoceancleanup.com/.

Lin, T.-Y., Maire, M., Belongie, S., Hays, J., Perona, P., Ramanan, D., Dollár, P., and Zitnick, C. L. Microsoft coco: Common objects in context. In *European conference on computer vision*, pp. 740–755. Springer, 2014.

Luo, W., Sun, P., Zhong, F., Liu, W., Zhang, T., and Wang, Y. End-to-end active object tracking and its real-world deployment via reinforcement learning. *IEEE transactions on pattern analysis and machine intelligence*, 2018.

Qiu, W. and Yuille, A. L. Unrealcv: Connecting computer vision to unreal engine. In *ECCV Workshops*, 2016.

Redmon, J. and Farhadi, A. Yolov3: An incremental improvement. *arXiv preprint arXiv:1804.02767*, 2018.

Thung, G. and Yang, M. Classification of trash for recyclability status. 2016.

Tobin, J., Fong, R., Ray, A., Schneider, J., Zaremba, W., and Abbeel, P. Domain randomization for transferring deep neural networks from simulation to the real world. In *Intelligent Robots and Systems (IROS), 2017 IEEE/RSJ International Conference on*, pp. 23–30. IEEE, 2017.

Tremblay, J., Prakash, A., Acuna, D., Brophy, M., Jampani, V., Anil, C., To, T., Cameracci, E., Boochoon, S., and Birchfield, S. Training deep networks with synthetic data: Bridging the reality gap by domain randomization. *arXiv preprint arXiv:1804.06516*, 2018.