Detecting Waterborne Debris with Sim2Real and Randomization

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Abstract

From palpable marine debris to microplastics, marine debris pollution has been a perennial problem. In recent years, there is an emergence of large-scale clean-up efforts making its way around the world. Complimentary to large-scale clean-up efforts, there is a nascent area in the use of unmanned and remote vehicles for detecting and removing debris. In this project, our focus is on marine debris detection where we propose to train a waterborne debris detector based on a mixture of real and synthetic training samples. We leverage on the capabilities of game engines to generate a variety of distributions and types of marine debris with variations in camera angles and distance from objects. The use of the game engine allows us to get segmentation masks at no expense as the ground truth is known. We further augment the images via domain randomization and mix with the real dataset. All our datasets and model implementations will be publicly available.

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.

This project aims 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 to encourage follow-up research in this direction.

2. Methodology & Evaluation

The real-world training data is from COCO (Lin et al., 2014) and (Thung & Yang, 2016) that contains 2527 images for different trash. We 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

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

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 and bags) with different appearances in the wild more robustly compared to those only trained on real-world images.

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

3. Preliminary Experiments

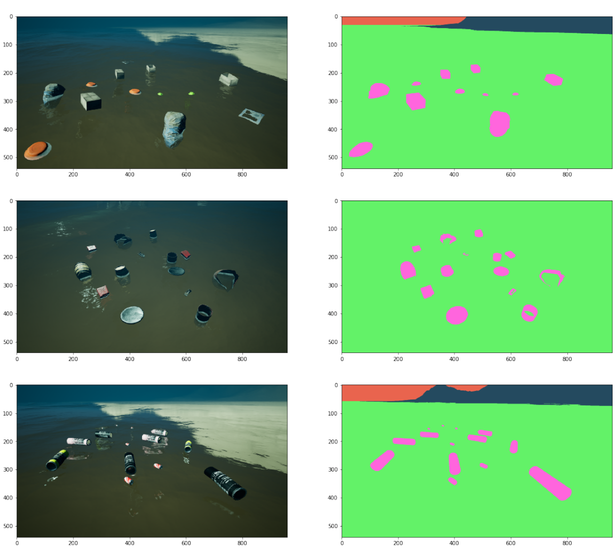

Figure 1. Images on the left are generated by our custom debris world, and images on the right are automatically generated segmentation masks.

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 customized debris world created through Unreal Engine 4, we can 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. The workflow of generating this synthetic dataset with domain randomization is illustrated in Figure 3. 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.

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.

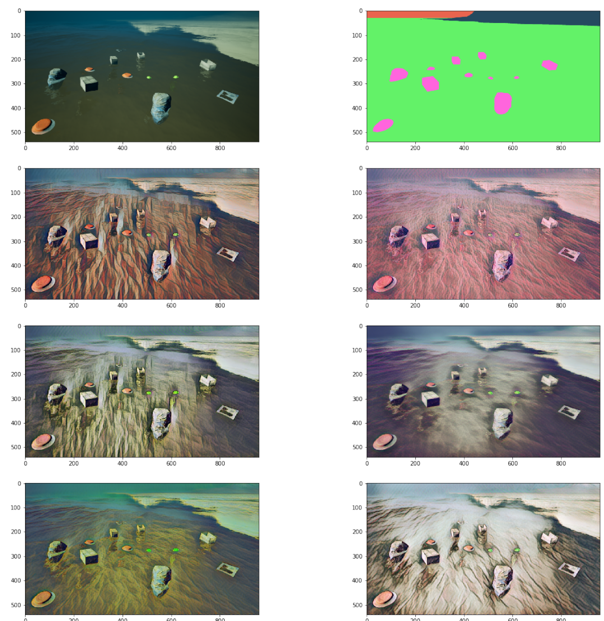

Figure 2. The top left image is the synthetic image of debris in the sea. The top right image is the segmentation mask. The remaining 6 images are domain randomization permutations generated from the original synthetic image.

4. 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.

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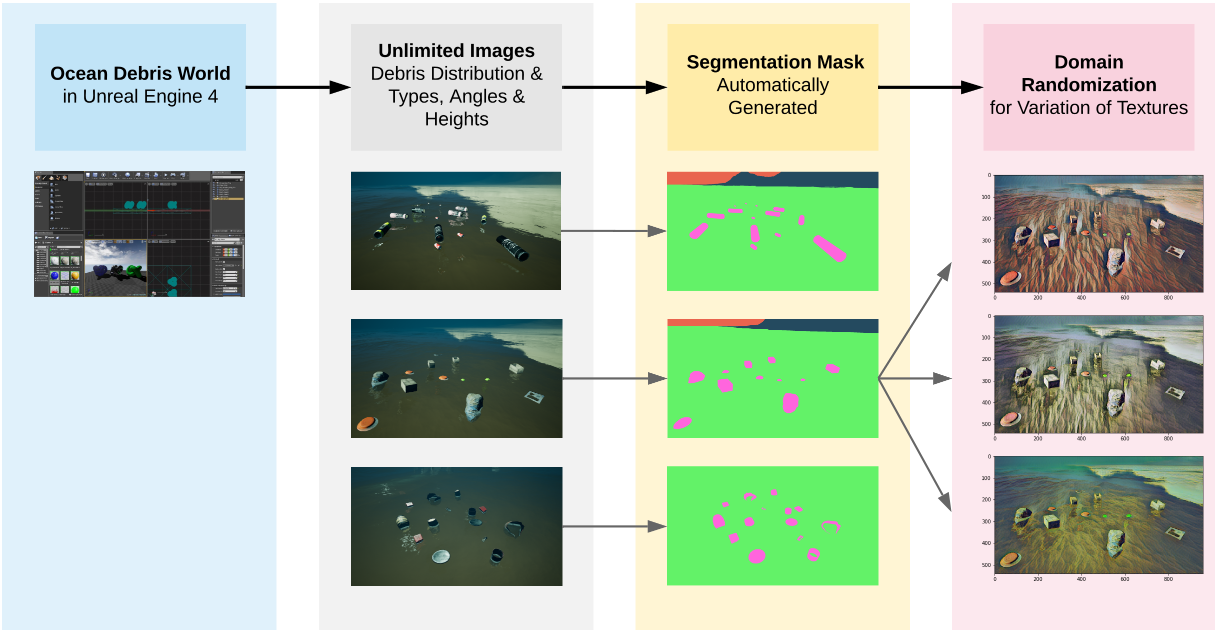

Figure 3. Workflow of generating synthetic ocean debris images with randomization.

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