SeaDroneSim: Simulation of Aerial Images for Detection of Objects Above Water

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Abstract

Unmanned Aerial Vehicles (UAVs) are known for their fast and versatile applicability. With UAVs' growth in availability and applications, they are now of vital importance in serving as technological support in search-andrescue(SAR) operations in marine environments. High-resolution cameras and GPUs can be equipped on the UAVs to provide effective and efficient aid to emergency rescue operations. With modern computer vision algorithms, we can detect objects for aiming such rescue missions. However, these modern computer vision algorithms are dependent on numerous amounts of training data from UAVs, which is time-consuming and labor-intensive for maritime environments.

To this end, we present a new benchmark suite, **SeaDroneSim**, that can be used to create photo-realistic aerial image datasets with the ground truth for segmentation masks of any given object. Utilizing only the synthetic data generated from **SeaDroneSim**, we obtain 71 mAP on real aerial images for detecting BlueROV as a feasibility study. This result from the new simulation suit also serves as a baseline for the detection of BlueROV.

Index Terms—simulation, aerial images, automation, BlueROV detection.

1. Introduction

Unmanned Aerial Vehicles (UAVs) equipped with high-resolution cameras and GPUs are increasingly used in a variety of tasks, ranging from precision agriculture[14, 18], crowd surveillance[7, 13], search and rescue (SAR) missions[3, 4, 8, 12]. With UAVs' growth in availability and applicability, they have recently gained a lot of attention, particularly in assisting in SAR and post-disaster area exploration missions by providing birdview over the scene.

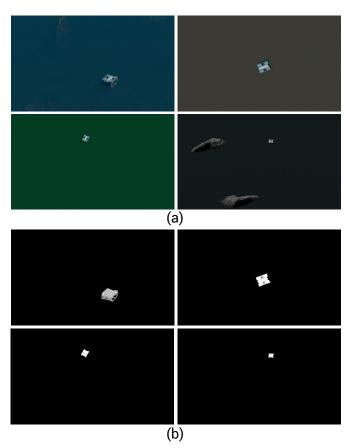


Figure 1. (a) Typical image examples with varying altitudes, angles of view and background watercolor. (b) Corresponding ground truth masks for the object of interest(BlueROV)

Specifically, in marine scenarios, where large ocean area needs to be quickly scanned and searched. In such cases, UAVs are of vital importance to provide effective and efficient aid to emergency search and rescue operations[22]. For such SAR missions, we would want a robust vision-based system to locate/track objects of interest in maritime environments with different lighting conditions, altitudes

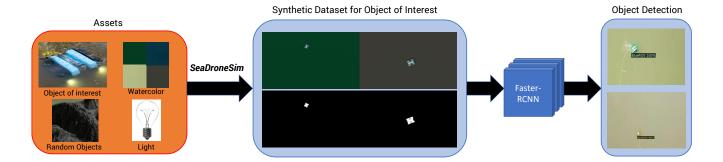


Figure 2. An overview of our approach: 3D models for the object of interest are used in *SeaDroneSim* to generate Synthetic datasets. Noted the synthetic dataset would include its ground truth mask for the object of interest. The synthetic dataset generated is then fed into a Neural network to obtain the object detection result. *Object Detection images are cropped and enlarged for better visualization*

of the image taken, viewing angles, and watercolors, Currently, most of these vision-based systems are data-driven systems employing deep neural networks. These systems are dependent on large-scale datasets to correctly recognize objects and be versatile to the changes in different environments. However, there are only a few datasets available and they are limited in their size and objects in the datasets. Even though Varga [19] proposed a relatively large dataset for the Maritime environment, there is still a great lack of large-scale datasets in maritime environments for a variety of objects. The process of collecting large-scale for specific object detection tasks is slow, time-consuming, and has poor scalability. Using such a manual approach, only a few objects of interest can only be located/tracked within a specific dataset for that task.

This work aims to fill the gap for the lack of large-scale maritime-based datasets captured from UAVs. We introduce a simulation suit for generating simulation images of maritime-based aerial images, called **SeaDronesSim**. We are capable of generating videos and images of any object of interest with the given 3D model in open water with various lighting conditions, altitudes of the image taken, viewing angles, and watercolors(see Fig. 1(a)). To fully utilize the {SeaDronesSim, the ground truth for the objects of interest is generated at the same time(see Fig. 1(b)). Most SAR missions require the vision-based system to be able to detect and track from a large distance, {SeaDronesSim is able to vary its resolution for the RGB footage captured. To study the feasibility of recognition of objects of interest from only the synthetic images generated from SeaDrones-Sim, we used BlueROV which we have at hand as the object of interest in our experiment.

Moreover, since it is a simulation, we have all the ground truth information of the aerial camera(altitude taken, rotation) and the BlueROV(rotation), we can also output all the metadata for the aerial camera and the objects of interest. We believe all this metadata could be used in the future to

develop multi-modal systems to improve accuracy or speed.

Finally, we conduct extensive experiments to compare the datasets that we generated using a state-of-the-art model and hereby establish baseline models for BlueROV detection. These results serve as a starting point for our *SeaDronesSim* simulation suit. The code of the *SeaDronesSim* will be released once the paper is admitted. To streamline the process of object detection, the goal is to utilize the advancements in robotics and artificial intelligence that can enable us to gather UAV-based aerial images from the maritime environment and then automate the process of object detection and tracking. To the best of our knowledge, *SeaDronesSim* is the first simulation for UAV-based aerial images from the maritime environment. Our main contributions are as follows:

- We propose a novel simulation suit for generating UAV-based aerial images for the maritime environment.
- To the best of our knowledge, we established a baseline for detecting BlueROV in open water.
- We open-source our SeaDronesSim and dataset associated with this work to accelerate further research.
- We proposed a pipeline for autonomously generating UAV-based maritime images for objects of interest and detecting them.

The rest of this paper is organized as follows: We will first place this work in the context of related works in Sec. 2. Then, we describe the proposed simulation which is used to create realistic images in Sec. 3. We then present some evaluations both quantitatively and qualitatively of our approach in Sec. 4. We will conclude our work in Sec. 5 with parting thoughts on future work

2. Related work

In this Section, we will first review some of the major datasets for aerial images and maritime environments. Then we will go through some of the simulations for the maritime/aerial domain.

2.1. Datasets for Maritime Environments

Large-scale datasets are of great necessity when developing modern computer vision algorithms. However, many datasets for maritime environments are satellite-based synthetic aperture radar imagery and are used for remote sensing tasks. Airbus[1] released 40k satellite images(with instance segmentation labels) from synthetic aperture radars for ship detection. Li et al[9] proposed Another dataset for ships consisting of mainly Google earth and partially UAV-based images. Later on, more UAV-based datasets are released, especially for SAR tasks. In 2019, Lygouras et al[11] works on human detection with UAV-based images. However, Lygouras' dataset has its limitation. The dataset is collected either near the shores or in the swimming pool. Another UAV-based images dataset, released by Varga[19]. is tailored towards the task of recognizing objects in water and collecting a large-scale dataset for the maritime environment. However, Varga's dataset only provides six classes of objects. There are a lot more objects of interest in the SAR tasks such as hovercraft, floating planes, humans waving for help and etc. There will be no such dataset that can represent all objects of interest for any detection task.

2.2. Simulation

Instead of collecting large-scale datasets for detection tasks, we follow the conceptual approach of detecting oysters[10] and propellers[16] which is to utilize the 3D model of the object to generate an enormous amount of data synthetically. In particular, we used a 3D model of the BlueROV to create a maritime dataset for BlueROV detection.

When there is a lack of large-scale datasets for some robotics tasks, different research groups have developed different simulations to meet their needs. Most simulators for the aerial and maritime domains are focusing on controlling the drone for safety operations[6] and rapid control[20]. Abujob[2] used simulation to verify his algorithm of landing the drone on the ship with the prediction of Ship Motion The most similar simulation to *SeaDroneSim* is from Matlab UAV Toolbox[17] which provides control of the drone and also images from a camera attached to the drone. However, this application focuses on the on-land work and does not provide segmentation ground truth for the object of interest. Their major focus is on controlling the drone as well.

With the ultimate goal of developing an autonomous UAV-based surveillance system, we acknowledge the need

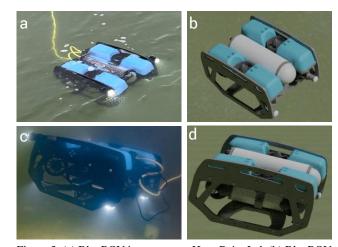


Figure 3. (a) BlueROV in water near Horn Point Lab (b) BlueROV in BlenderTM (c) BlueROV in water in Horn Point Lab (d) BlueROV in BlenderTM

for object detection methods. Moreover due to the lack of large-scale datasets for the maritime environment and the lack of literature addressing this problem we are seeking an alternative path for generating maritime environment datasets by looking into synthetic image generation. To the best of our knowledge, we are the first to propose a simulator(SeaDroneSim) for maritime environment datasets and use that dataset to recognize objects of interest. SeaDroneSim will be described in the next Section.

3. Proposed Approach

In this work, we propose a novel simulation built from BlenderTM[5] game engine. Then we used the simulation for creating UAV-based maritime images which are then used to train a Neural Network for object detection. In this section, we will talk about our proposed approach (which is summarised in Fig. 2). We will go through some of the details of the implementation of the *SeaDronesSim*.

3.1. Object of Interest

One of the most important things in this work is the accurate 3D model of the object. Only with an accurate 3D model of the object in the simulation, we can then correctly represent the visual appearance from the UAV-based maritime images. In this work, we used a 3D model for the BlueROV. As we can see in Fig. 3, the 3D model in the simulation(Fig. 3(b)(d)) looks very similar to real BlueROV in the water(Fig. 3(a)(c)). Although there might be some visual difference between the images from the real data and the synthetic data, the actual object size in the UAV-based image is relatively small and we can neglect the visual difference here. The relatively small size of the object in UAV-based images makes it possible for rendering the datasets in SeaDronesSim. And directly used the datasets for training a network on detecting the real object.

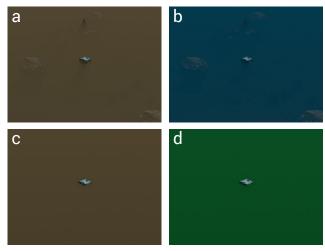


Figure 4. Different watercolors and turbidity levels

3.2. Water Volume

The major distinction between an on-land simulation and a maritime simulation is the water volume. In BlenderTM environment, the render engine "CYCLE" uses path-tracing of the lights to generate images. In other words, it passes light with a certain number of bounces and receives light to generate images of different brightness, colors, and shades. By customizing particles in the water volume, we get a photo-realistic maritime image for different watercolors and turbidity levels. The color of the volume can also be modified to mimic a specific maritime environment's color scheme. As we can see in Fig. 4(a) and Fig. 4(b), these are UAV-based maritime images of different watercolors in low turbidity. As we increase the turbidity level for the water, the object we added at the bottom(visible in Fig. 4(a)) is no longer visible in Fig. 4(c). Another image with different watercolors in high turbidity is shown in Fig. 4(d).

3.3. Aerial Image

We want to simulate the aerial Images in SeaDroneSim. However, we do not care about the UAV's appearance and its physical model. The only thing that we care about is the camera attached to it. So we basically modeled the drone as a point object with a camera attached to it(we will just refer to the point object as the drone). Instead of moving the drone or the object in the simulation, we choose to move the object and fixate the camera on the object. In this case, when the object is closer to the drone, the object will look larger so that we can obtain multiple sizes within one run. However, this will not cover all possible sizes that we may want, so we adjust the altitude of the drone to obtain different images. As we can see in Fig. 5, the object and its corresponding ground truth mask in the image become smaller when we increase the altitude when taking the images. The resolution of the image could go up to 30000

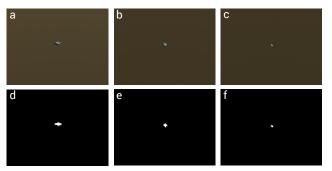


Figure 5. Images from different altitudes. (a) image from an altitude equal to 20m, (b)image from an altitude equal to 30m, (c)image from an altitude equal to 30m, (d)(e)(f) are the corresponding ground truth masks for (a)(b)(c)

pixels by 30000 pixels which are dependent on the computational power of the hardware that is running the simulation.

3.4. Object not of Interest

To simulate some of the scenarios in that some objects not of interest are included, we add a few objects at the bottom of the seafloor and some of the hills are over the sea level as we can see in Fig. 1(a).

4. Experiments and Results

We perform a comprehensive comparison with various training data by utilizing Faster R-CNN [15]. By rendering the training data in SeaDroneSim, it can provide tremendous images under different sizes, depths, angles, and colors. We resized the images to 416x416 pixels. For each masked image, the bounding boxes can be determined by the highest and the lowest x and y coordinates of BlueROV in the image. With these x and y coordinates, we added a BlueROV category and the corresponding bounding boxes. Therefore, each image receives a LabelMe format JSON file. After running through all images in the folder, we transformed the JSON file from LabelMe to coco format for preparing the training dataset. Instead of implementing a Faster R-CNN model from scratch, we used Detectron2 [21] which allows us to accelerate the developing process. Detectron2 is a novel system created by Facebook AI Research (FAIR) for computer vision research such as object detection and segmentation.

4.1. Train/validation splits

There are six kinds of training datasets in the experiments. For all the images from the simulation, we took 80% for training and 20% for validation. We separated the experiments into two parts. The first part was to find out the difference between different depths. There were 626 images with the same color in each depth containing one

BlueROV. Fig. 5 shows the depth images in the training dataset. To avoid the influence of noise, we removed the environment in the simulation. Therefore, there were not affected by other factors except for BlueROV. In the second part, we created a few datasets with different watercolors in the simulation environment. There were 626 images for each color with multiple angles and depths in the maritime environment. Fig. 6 shows the example images of different watercolors in the training dataset. We could mimic the real UAV-based maritime images by modifying the watercolors and adjusting the altitude for the image taken.

4.2. Base model

In this experiment, we used Faster R-CNN with X101-FPN as our backbone to train our dataset. Though X101-FPN takes longer time and more memory during training, it can obtain higher accuracy results compared to other models in Faster R-CNN. That is the reason why we preferred to choose this model to achieve this experiment. In the model, we set up the learning rate of the model as 0.001. To prevent overfitting, the maximum number of iterations is determined as 1500, which can be adjusted according to the performance of validation. As we only focused on detecting BlueROV in the image. Hence, there is only one class in this recognition task.

With dataset and model, it is convenient to train custom models in Detectron2. Registering the coco instance function, we uploaded training, validation, and testing data to the Detectron2 platform. Then we created a class and imported Faster R-CNN as our training model. get_cfg function could allow us to access the parameter of the model. From this function, we can assign the value to the parameter. The checkpoint and weight were saved in the file path which cfg.OUTPUT_DIR was written. The checkpoint was provided to us to continue training the data after interrupting the training process.

4.3. Evaluation

To prevent the convolutional neural network from overfitting to the synthetic dataset for a relatively easy task, we did not provide a large quantity of training data. However, these training data performed at least 95% AP in the validation. Therefore, the next step is to evaluate the testing data. Testing data was collected from Sandy Point Park in Annapolis, MD. Fig. 7 shows some of the real UAV-based maritime images. We used DJI pro2 and took a few video clips. We then carefully labeled 2000 image frames selected from the video as the testing data to produce convincing results.

Table 1 displays the output of evaluating testing data with different training data obtained from various altitudes. Samples images of images taken from altitudes 20m, 30m, and 40m and be seen in Fig. 5(a), Fig. 5(b), Fig. 5(c) re-

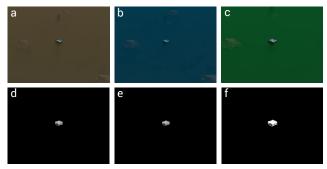


Figure 6. Examples of original and ground truth mask images. These examples are based on different colors dark brown, light blue, and green consecutively.

spectively. The highest mAP is 54.19 when the depth is under 30 meters. Although depth 20 images are clearer in the simulation view, the certain size of BlueROV may result in lower accuracy to detect smaller drone in the testing images. Therefore, depth 30 meters contribute to the higher accuracy to match the testing data compared with others.

Table 2 performs the evaluation between different colors training. As shown in Fig. 6, we applied three watercolors: brown, blue, and green. We will just name these three datasets by their color for simplicity. Each color of training data contains different sizes and angles of BlueROV as we have mentioned in Sec. 3.3 to evaluate the result. The highest mAP in Table 2 is from training data brown with 71 mAP. Some of the results are displayed in the second row of Fig. 7. Furthermore, blue data also achieves a similar score with 69.44 mAP. This result may be caused by our data collected from Sandy Point Park being closer to the color brown. Hence, brown train data can detect robust performance compared with other colors. Result obtained from dataset green has the worst performance as we suspect that the color does not match the maritime environment.

The outcome between Table 1 and Table 2 exists a large gap. The highest mAPs of the two tables are 54.19 and 71 mAP separately. The possible reason is that there are some

Table 1. Training data with various depths

| Train data | AP | AP_{50} | AP_{75} | AP_s | AP_m |
|--------------|-------|-----------|-----------|--------|--------|
| altitude=20m | | | | | |
| altitude=30m | 54.19 | 98.32 | 52.84 | 54.24 | 54.78 |
| altitude=40m | 52.20 | 97.23 | 51.86 | 52.41 | 47.82 |

Table 2. Training data with different colors

| | Train data | AP | AP_{50} | AP_{75} | AP_s | AP_m | |
|--|------------|-------|-----------|-----------|--------|--------|--|
| | brown | 71.00 | 96.42 | 87.24 | 70.94 | 80.08 | |
| | blue | 69.44 | 96.91 | 84.86 | 69.39 | 74.52 | |
| | green | 65.09 | 98.35 | 77.75 | 64.58 | 82.76 | |



Figure 7. The first row is the examples of testing images. The second row is the testing results for the above images. These examples are collected from Sandy Point Park in Annapolis, MD.

depth training data is covered by the sea level. With losing approximately half of the feature of the BlueROV, training data in the outcome between Table 1 may reduce its confidence to detect BlueROV. In contrast, Table 2 collects the whole view of BlueROV with different colors, depths, and angles in the training data, which improves the recognition rate in the testing data and obtains a much higher mAP than Table 1.

5. Conclusion and future work

In this work, we fully utilized the capability of a game engine and built a simulation for rendering UAV-based maritime images. We discussed some of the implementation details for . One of the 3D models for the object of interest, BlueROV, is used as a feasibility study for the systematic automation approach for rendering UAV-based maritime images and then detection. We then compared our detection result with the usage of different synthetic datasets generated from the simulation. With only the usage of the generated synthetic dataset, we then set the benchmark for detecting BlueROV in maritime UAV-based images as 71.00 mAP. These results highlight that for data-critical applications when collecting real images is challenging, it is possible to use 3D model of the object to create photorealistic images that will successfully detect objects in a specific domain. To the best of our knowledge, this is the first attempt to build a UAV-based maritime image simulation focusing on object detection. Being the first work in this field, there are many directions and possible improvements that can be made to our SeaDroneSim framework. One possible future work would be obtaining the various 3D models for SeaDroneSee[19] datasets and then rendering the datasets in *SeaDroneSim*. It shall further increase *SeaDroneSim's* utilization scenarios and prove the practicality of our simulation. As for the detection phase, we adopted the existing network. New network architectures can be developed to tackle the UAV-based maritime domain problem. Finally, more object noise can be introduced into the simulation for more robust detection.

6. ACKNOWLEDGMENT

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