Simulation Based Oyster Detection

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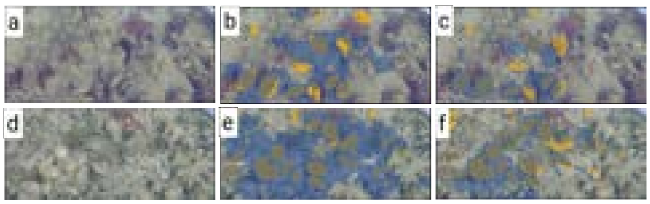

Fig. 1. Each row left to right: Input image, the output of the network when trained using only real data, the output of the network (which we call *OysterNet*) when trained using real data augmented with our synthetic data. Yellow represents the oyster segmentation ground truth and blue is the predicted segmentation result. Notice how the number of false positives and false negatives drop significantly when the training data is augmented with our synthetic data

Filter feeders, oyster reefs have significant advantages for the benthic marine ecosystem(s), including boosting species richness and offering habitat, sustenance, and protection for a wide range of marine organisms. However, overfishing, climate change, and the impact of diseases over the 19th century led to a dramatic decline in the standing stocks of oysters near the Chesapeake Bay and the North Sea. Massive efforts are being made to restore oyster habitats throughout the United States and Europe to address this terrible ecological issue.

Effectively tracking the development of oyster restorations is one of the main obstacles to advancing, improving, and adapting the restoration process. For the purpose of evaluating oyster reefs, Michael W. Beck advocated standardizing monitoring measures, units, and performance criteria. To ascertain the health of oyster habits, the number of environmental factors including water salinity, temperature, and dissolved oxygen are being tracked. In the literature, general metrics for oyster reefs are tracked, including "reef areal dimensions, reef height, oyster density, and oyster size-frequency distribution."These measurements, however, rely on the identification and counting of oysters, which is now primarily carried out by skilled human labor. Such a procedure is cumbersome, sluggish, and poorly scalable.

The oyster reefs can only be observed manually in a small area with few samples, such as 100 oysters per sampling site. Additionally, the material for the oyster's surface is similar to the seabed sediment. It is also very difficult to train new people or algorithms to perform oyster counting because it differs greatly from the washed oysters. To streamline the process of oyster mapping, the goal is to utilize the advancements in robotics and artificial intelligence that can enable us to gather images from underwater Remotely Operated Vehicles (ROVs) and then automate the oyster detection and density calculation. The creation of an oyster detection system is the key step in this process. In this study, we provide a mathematical model to produce oyster models and go on to employ generative adversarial networks to facilitate the sim-2-real transfer. To the best of our knowledge, this is the first attempt to geometrically model oysters. The contributions of this paper are as follows:

- We propose a novel mathematical model for the 3D shape of oysters.
- We simplify the geometric model of an oyster for the projection on the image plane which is used to generate photorealistic synthetic oyster images. These images are used to train a deep segmentation network *OysterNet* for oysters that achieves the new state-of-the-art.
- We open-source our oyster generation model and dataset associated with this work to accelerate further research.

In this experiment, we train on O_{real} (our real dataset) and test using *OysterNet* and Behzad Sadrfaridpour (DCO in the table) methods on O (our held-out real dataset). The Intersection over Union (IoU) scores are 18.16% and 18.88% respectively which serves as the baseline for oyster segmentation results for our dataset. Both techniques perform similarly in these cases.

Then, we wish to evaluate the performance using solely the produced synthetic dataset for training(O_{syn}).We use both techniques to train on O_{syn} and test on O. The IoU score is lower than our baseline at 7.45% and 6.47% , respectively. Although the network has acquired the ability to detect oysters in the synthetic domain, the transfer from the sim to the actual world is still lacking. For training, we combine a tiny quantity of real data with synthetic data($O_{syn\_and\_real}$). In comparison to the expert human labeled ground truth, we acquire a state-of-the-art IoU Score of 24.54%, which is 35.1% better than utilizing only actual datasets for training and 12.7% better than DCO when trained on synthetic augmented real data.

TABLE I
SEMANTIC SEGMENTATION RESULTS

Method	Train Data	Test Data	IoU Score(%)
DCO	O_{syn}	O	6.47
DCO	O_{real}	O	18.88
DCO	$O_{syn\_and\_real}$	O	21.76
OysterNet (Ours)	O_{syn}	O	7.45
OysterNet (Ours)	O_{real}	O	18.16
OysterNet (Ours)	$O_{syn\_and\_real}$	O	**24.54**