Detecting Potential Mussel reef in ROV Videos using deep learning

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Introduction

Blue mussel reefs are listed as biogenic reefs in the Habitat Directive of the European Union. They can protect shorelines and function as habitats for many marine creatures, but they are in danger. To protect existing mussel reefs, it is necessary first to find mussels and then map them to confirm that they form a mussel reef. DTU Aqua uses ROV(remotely operated vehicle) to film seabed and map mussel reefs based on ROV videos.

We propose one method based on YOLO(You Only Look Once) algorithm to detect mussels in the videos, roughly estimate their coverage automatically, and indicate potential mussel reefs. Additionally, one dataset, including 1000 labeled mussel images, was constructed to bridge the gap in marine datasets.

Problems

- Manually marking mussels in a large volume of videos is time-consuming and labor-expensive.
- Apart from detecting mussels, their coverage is also needed. Because the two identification criteria for mussel reef:
  - The seabed coverage by mussels is at least 30%,
  - The area of the seabed with mussels covers at least 2500 square meters.
- Except for ROV videos, exact GPS location, odometer data, and camera information are unavailable.

Data Collection

In this year's summer, some students in DTU Aqua, with the assistance of local volunteer fishermen, used ROV to film the seabed in Roskilde Fjord and collected nearly 70 videos.

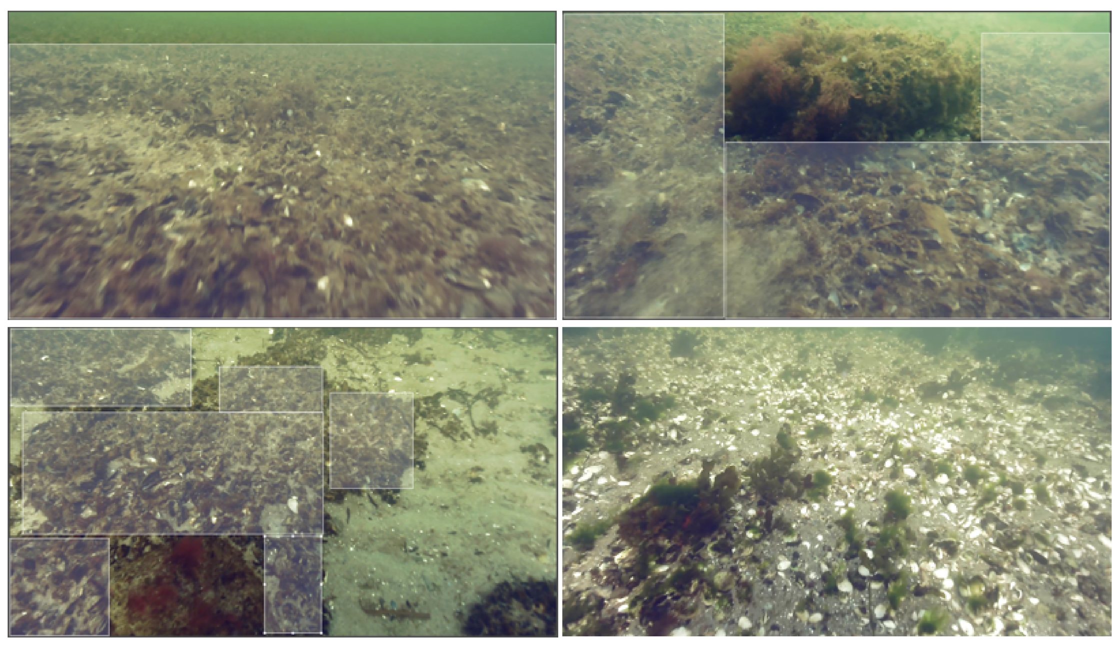

Figure 1: Some frames in output video

These videos are used to construct one mussel dataset, including 1000 1280x640 images. We extract the frames with mussels in the videos and label the mussels in the image using the tool: Labelimg. Four examples shown in Figure 1.

Methodology

Finding mussel reefs in one area can be transferred to finding mussel reefs in one video because each video was shot in one place and any periods in the video corresponded to one specific area. As we all know, One video contains many frames, and each frame is one image, as shown in Figure 2.

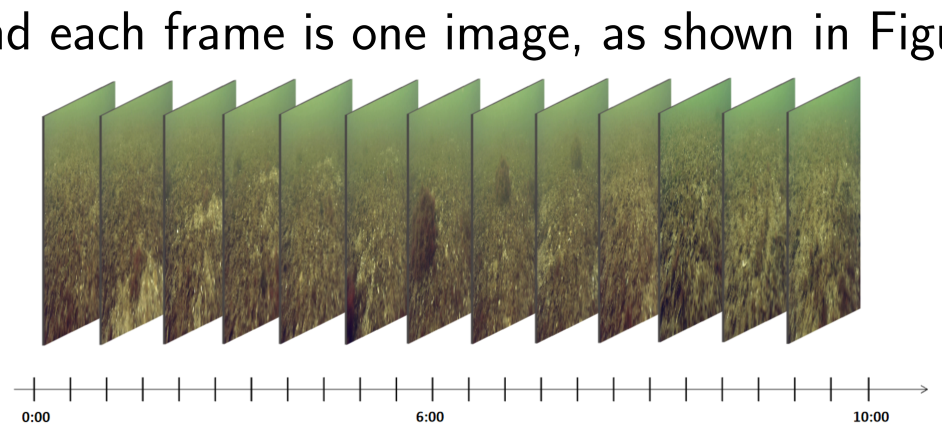

Figure 2: Frames in one video.

In one image, the mussels can be detected using YOLO algorithm and marked with rectangles. As the mussels are marked by rectangles, the rectangles' area can be simply seen as the area of mussels, and the area of the image is seen as the area of the seabed. Therefore, the coverage of mussels in one image can be roughly estimated using pseudo Equation 1. Because the boundary of mussels is irregular which is hard to fit by lines, we also tried the image segmentation method.

$$Mussel\ coverage = \frac{Mussel\ area}{seabed\ area} = \frac{Rectangle\ area}{Image\ area} \tag{1}$$

The mussels' coverage in all frames can be estimated using the equation. With the result, one graph, X-axis as time and Y-axis as coverage, will be generated to present the distribution of mussels in the video. After analyzing all the videos, the graphs will tell researchers which video likely includes one mussel reef, which means the corresponding area likely exists one mussel reef.

Experiment

In the experiment, we modified YOLO algorithm to enable to estimate mussels' coverage. Training parameters: GPU: Tesla 100, batch-size: 64, epoches: 200.

- **Train model**

The mussel dataset is divided into two parts randomly, 800 images were preprocessed and used as train dataset for training, the rest 200 images were used as test dataset for testing. Models performance shown below:

Type	Model	Precision	Recall	mAP 0.5
Detect	YOLOv5s	0.8	0.76	0.78
Segment	YOLOv5s	0.86	0.80	0.73

- **Detect mussels and estimate mussels' coverage in videos**

We chose one 20-minute video which filmed one potential mussel reef in Roskilde Fjord as input and used the trained model to detect the mussels in the video and calculate their coverage. Figure 3 shows some frames extracted from the processed video. The detecting speed is around 15 FPS.

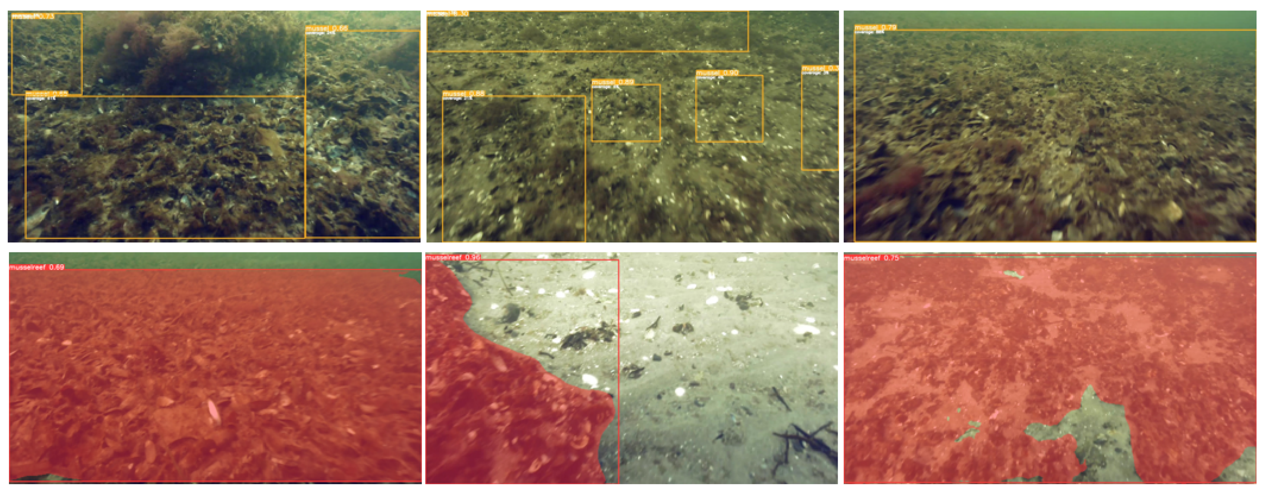

Figure 3: Some frames in output video

- **Result Visualization**

Using the mussels' coverage in each frame in the video, one graph was generated as shown in Figure 4. Considering readability, the unit of time(X-axis) is adjusted to minute instead of second or frame and the Y-axis is the mean of all frames' coverage in one minute, as the length of the video is very long and the amount of frames is large.

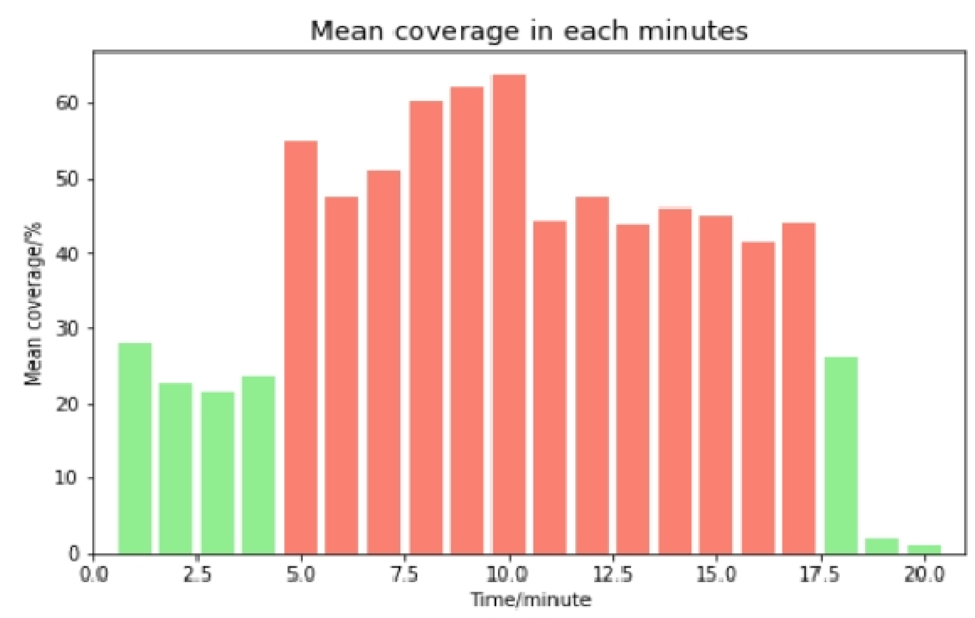

Figure 4: Some frames in output video

According to Figure 4, the mean coverage keeps higher than 40% from 5 minutes to 17 minutes while that of the first 5 minutes and the last three minutes is lower than 30 %. Therefore the corresponding area between 5:00 and 17:00 is likely exists one mussel reef.

Conclusion

In this project, we constructed one mussel dataset to bridge the gap in the marine datasets, proposed one method based on YOLO algorithm to detect mussels and estimate their coverage, and trained one model to implement the function. There are two advantages of our method:

- Low-cost. our method is not complex and requires fewer sensors, one camera is enough.
- Easy to deploy in ROV and real-time detection. Used models need little memory, around 120 MB, and detecting speed is around 15 FPS, reaching real-time speed.

However, the coverage estimation is imprecise, it is easily affected by shooting angle, uncertain scale, and disparity.

Our method provides the possibility for local volunteers without background knowledge to collect underwater videos when they are boating on the sea. The videos and the analysis result will be transferred to DTU Aqua. Based on the result, researchers can conduct related aquatic research on potential mussel reef areas directly instead of spending long time and manpower filming all the seabed in Roskilde Fjord and finding potential mussel reefs in numerous videos.

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