Time and Cost-Efficient Bathymetric Mapping System using Sparse Point Cloud Generation and Automatic Object Detection

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Bathymetry: Potential Applications

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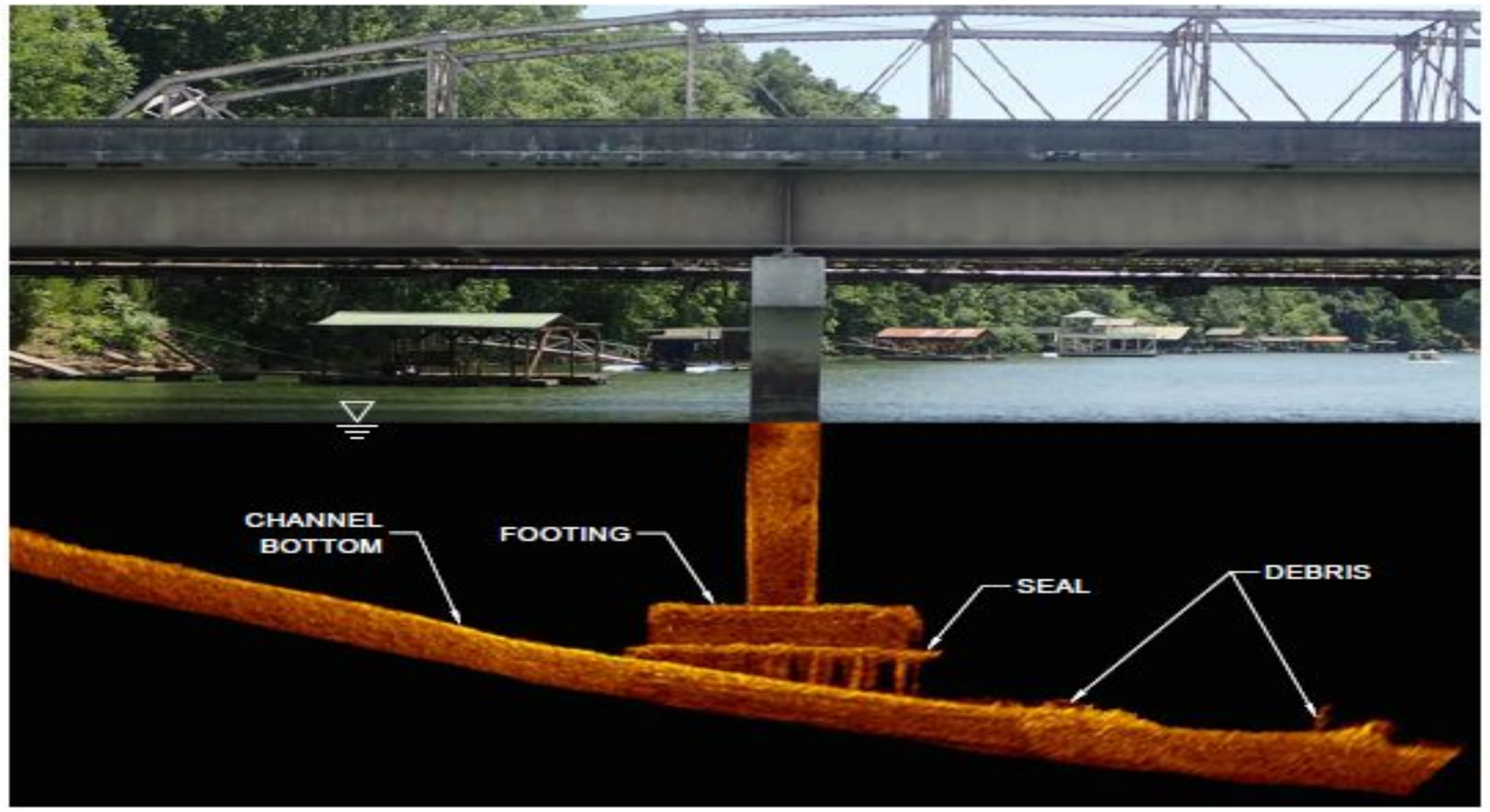
Artificial object inspection (pipes, bridges)



Source: Tennessee Department of Transportation

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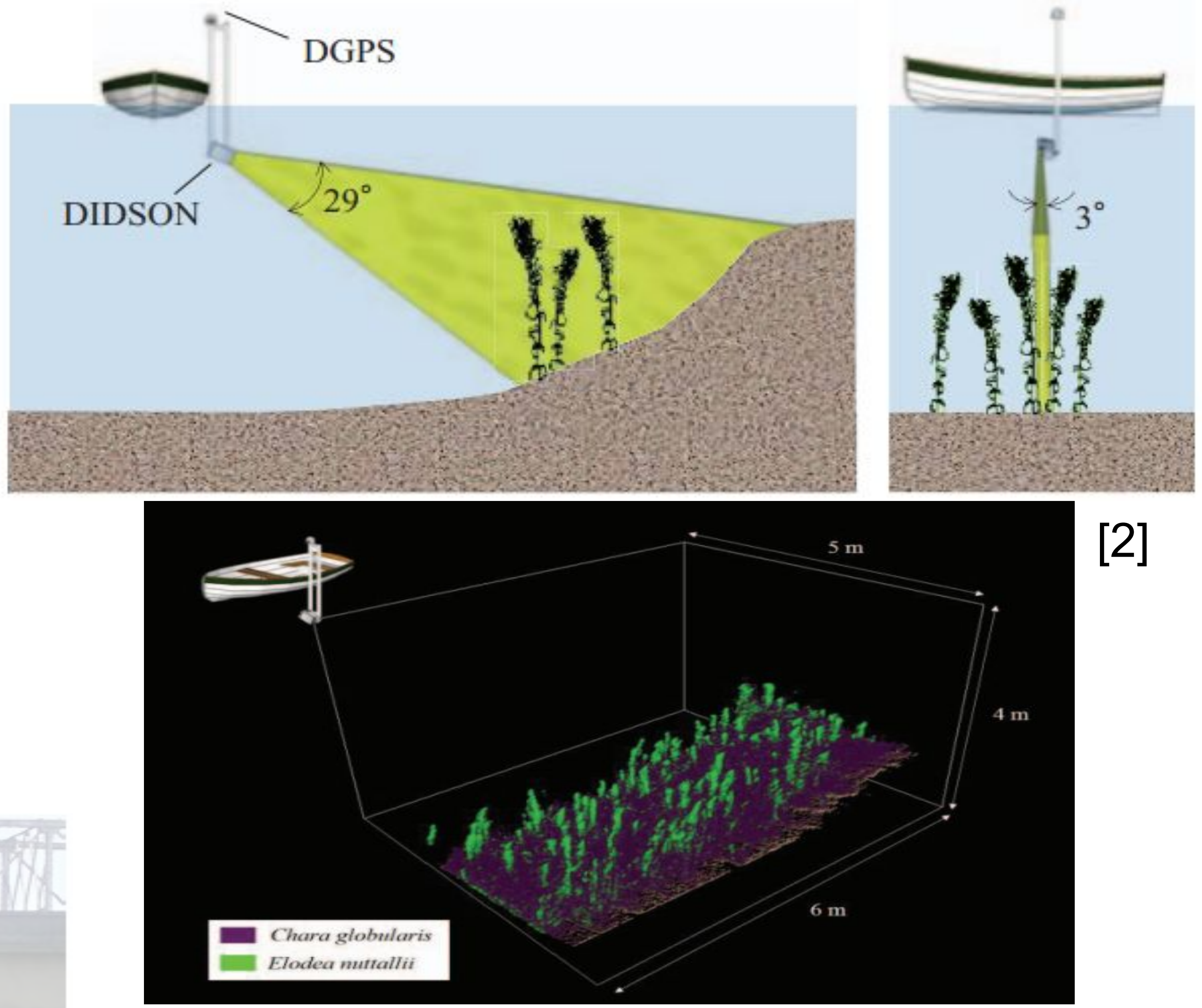

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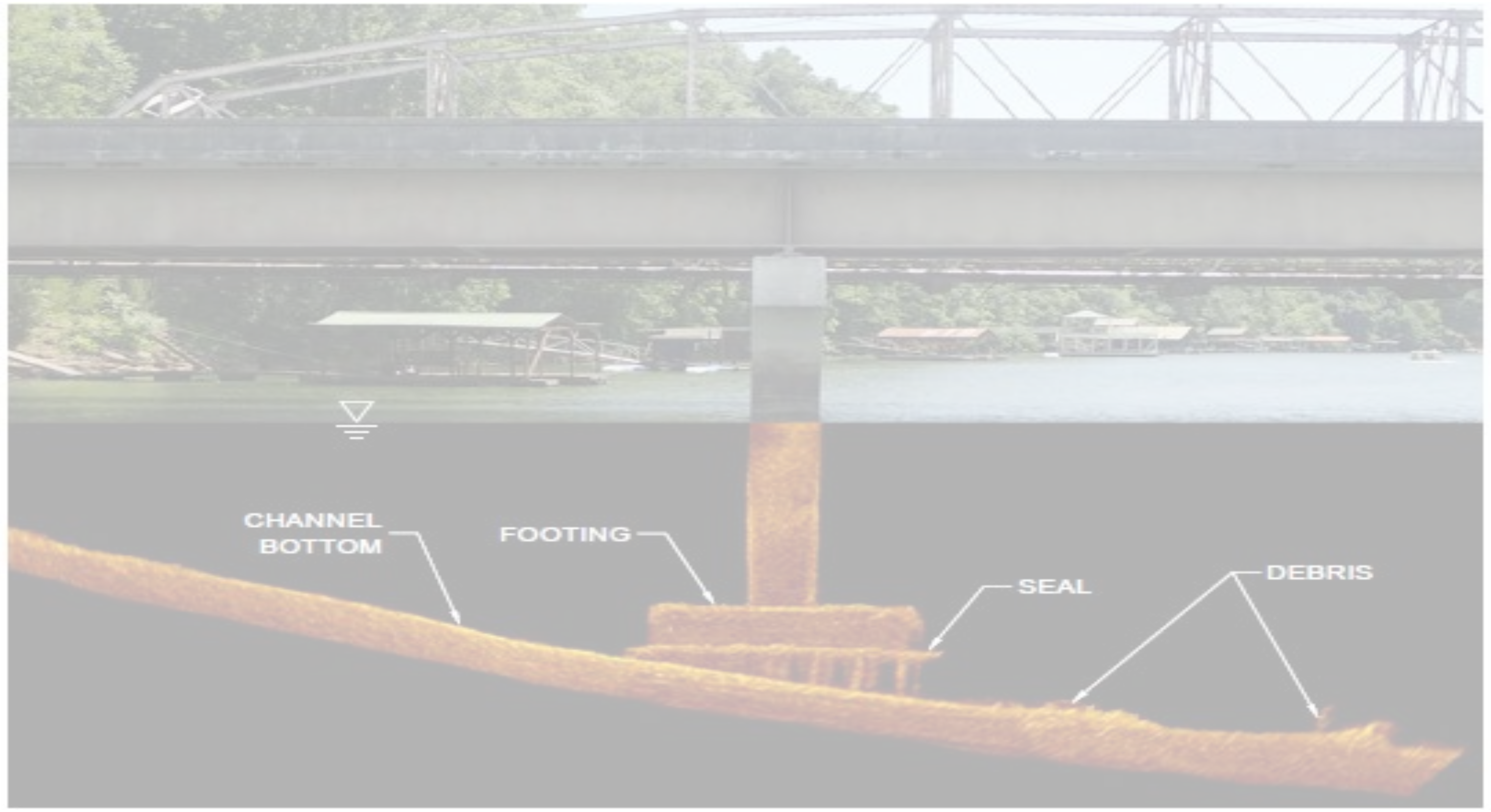

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Survey of aquatic plants

[3]

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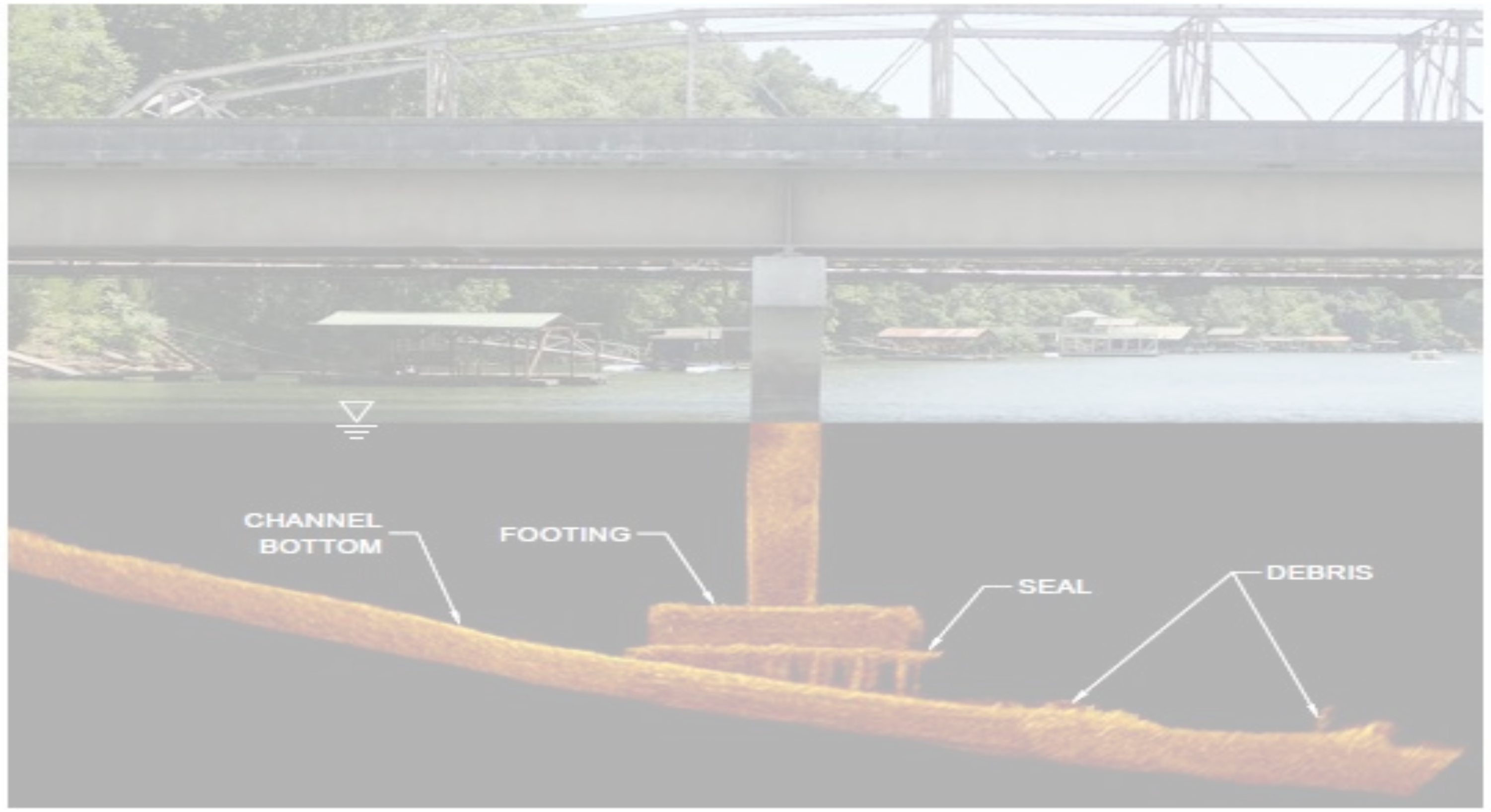

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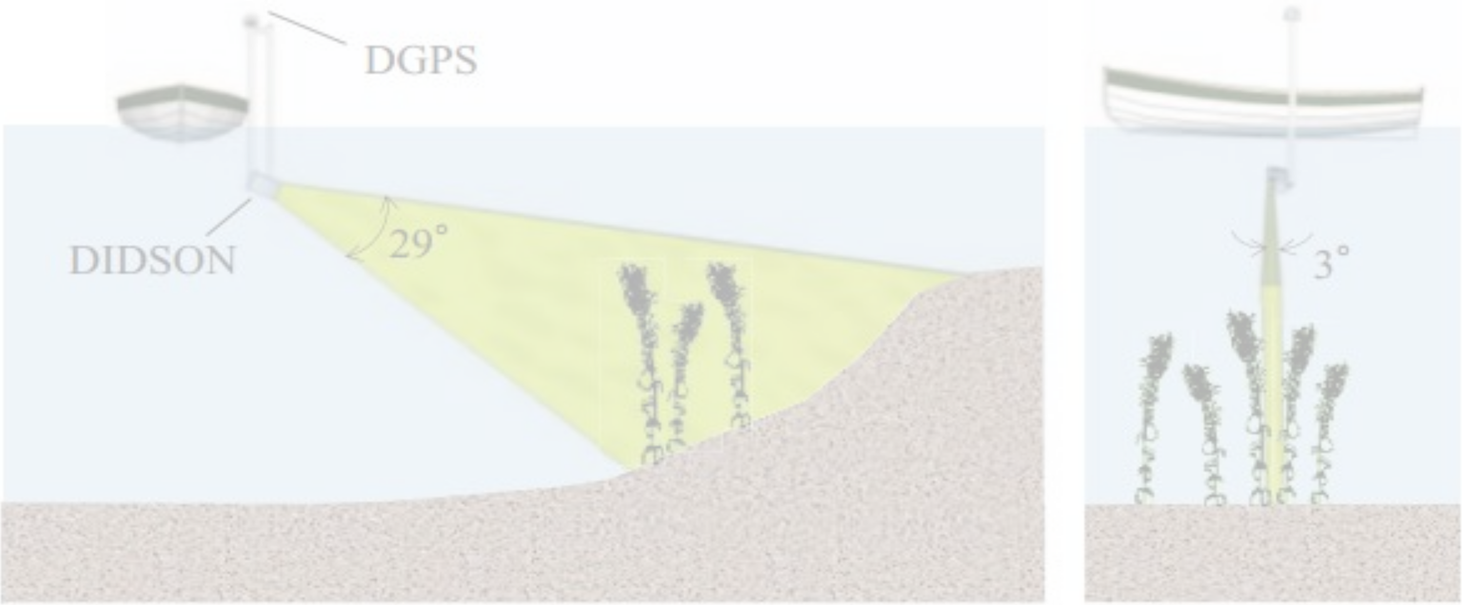
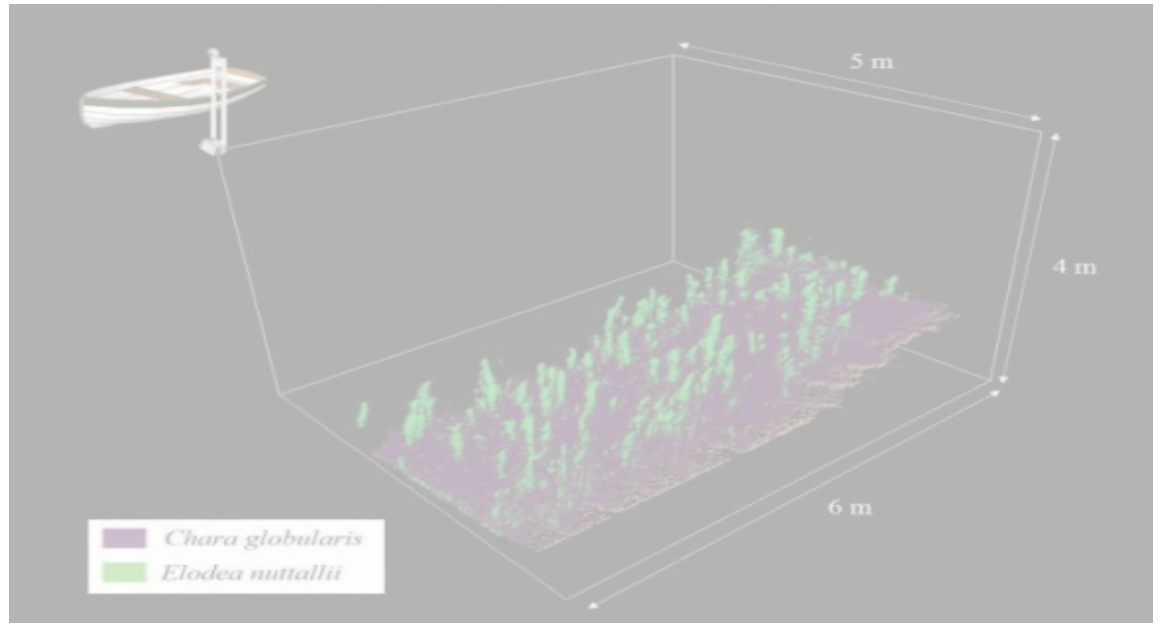
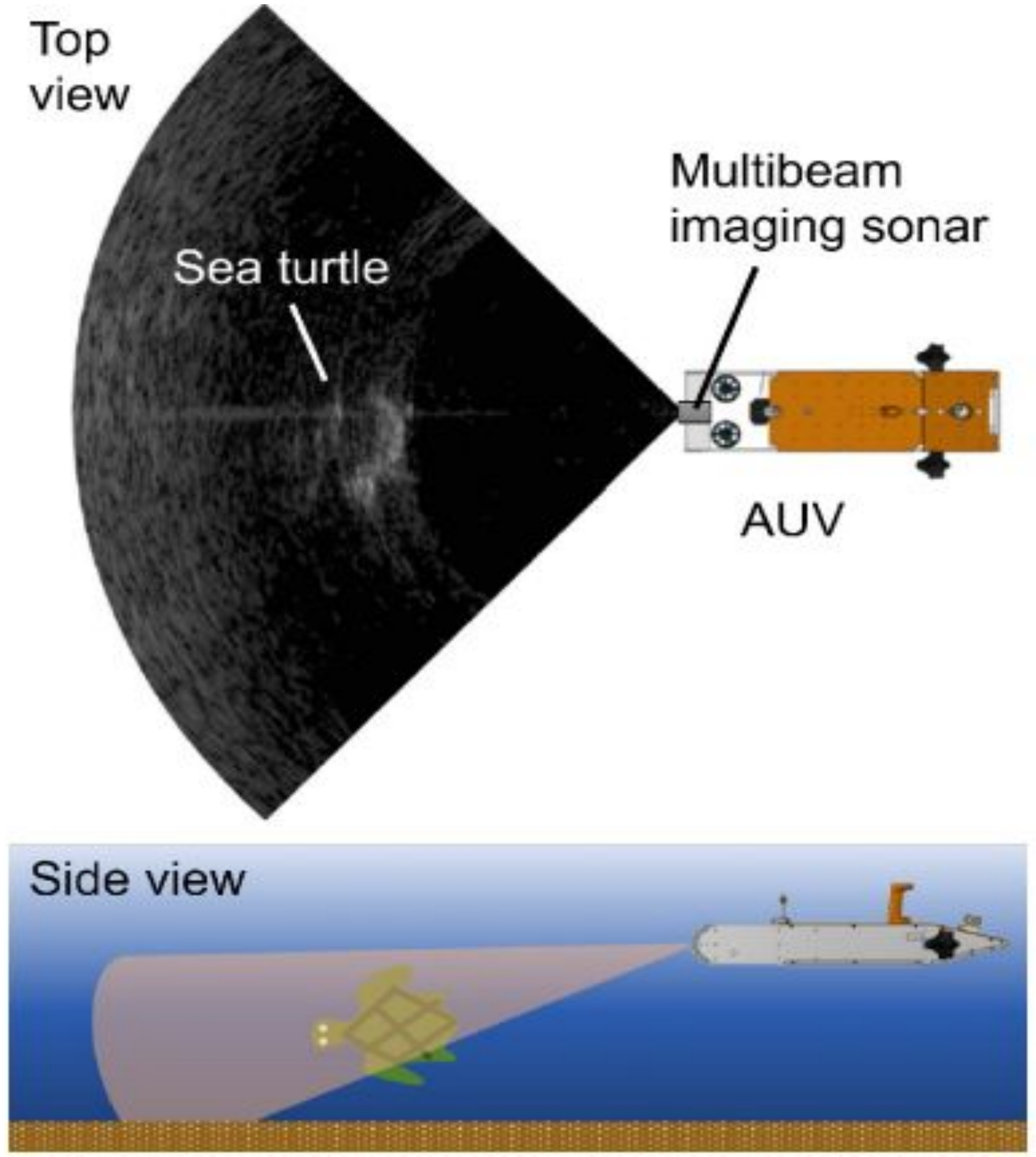




[2]

- Survey of aquatic plants

Survey of marine life



[3]

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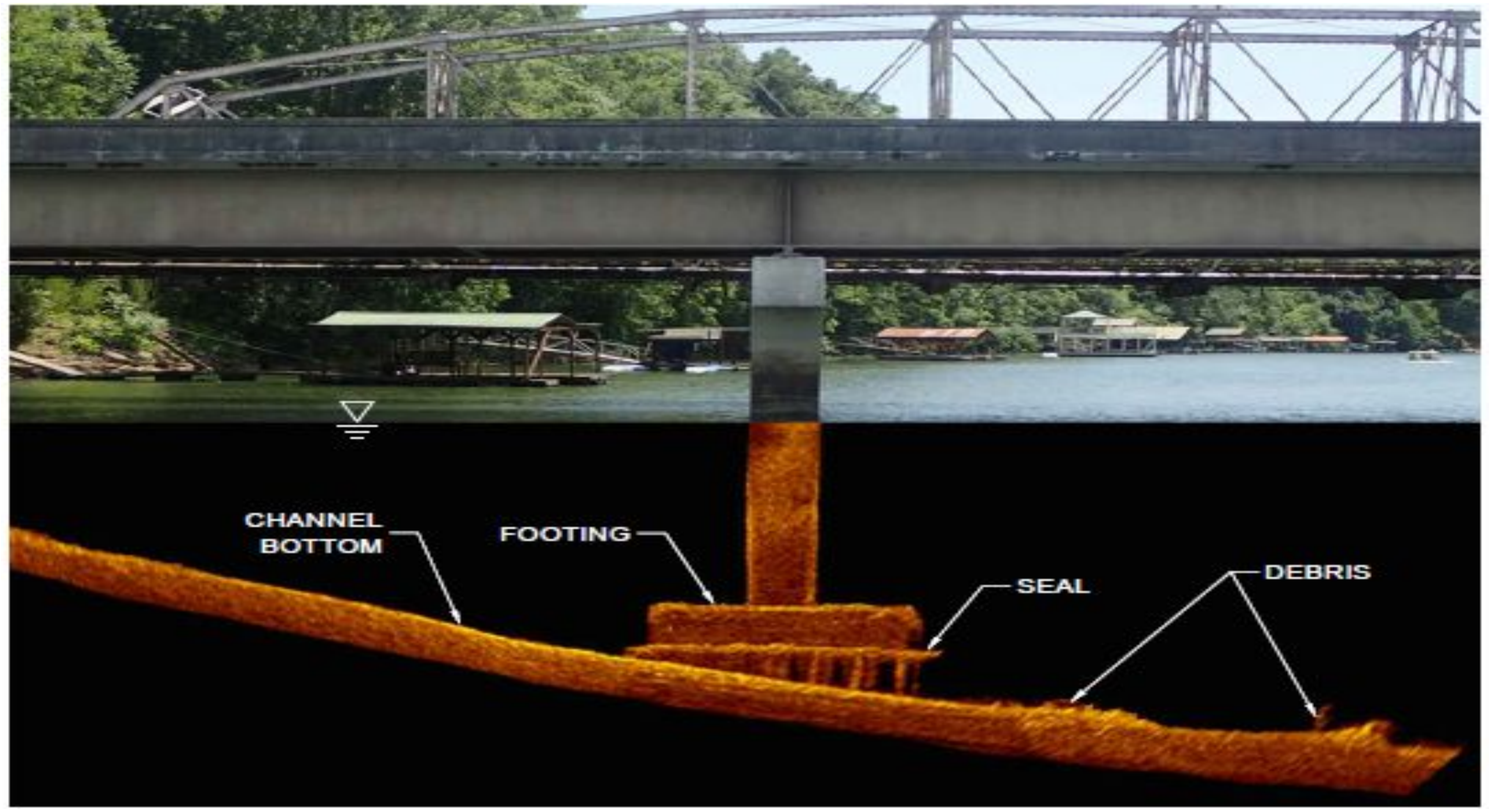
Artificial object inspection (pipes, bridges)



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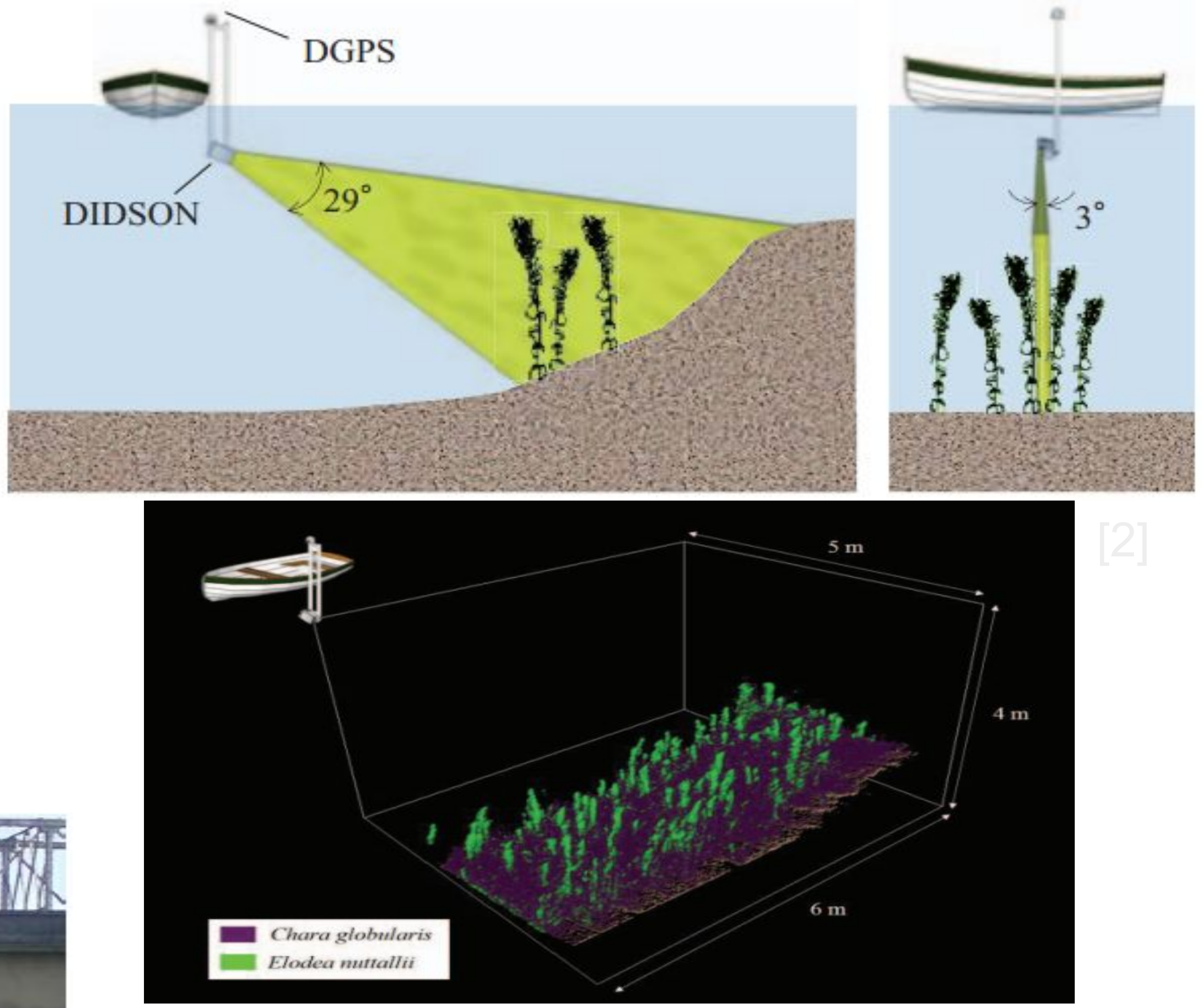

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Survey of aquatic plants

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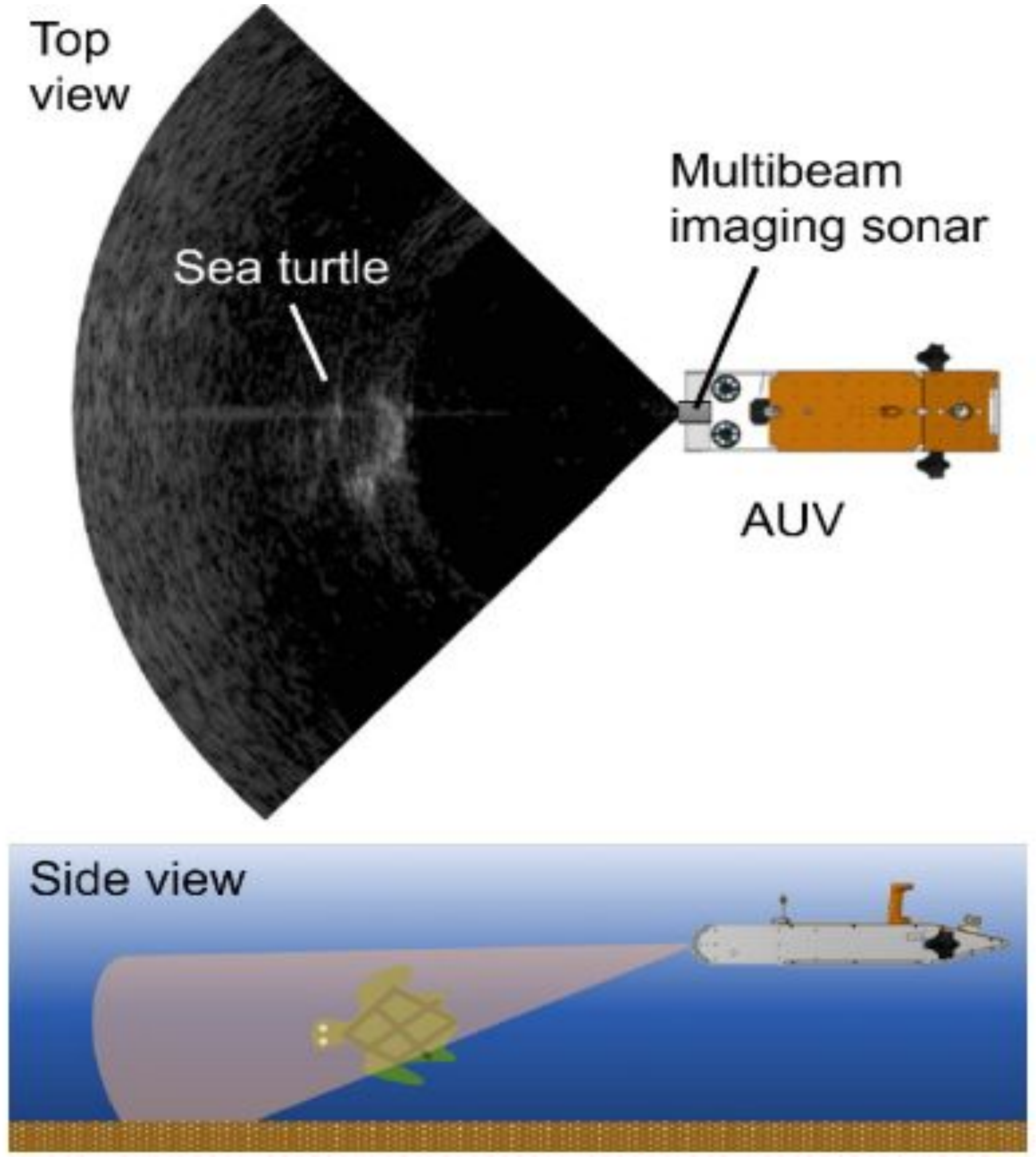


[3]

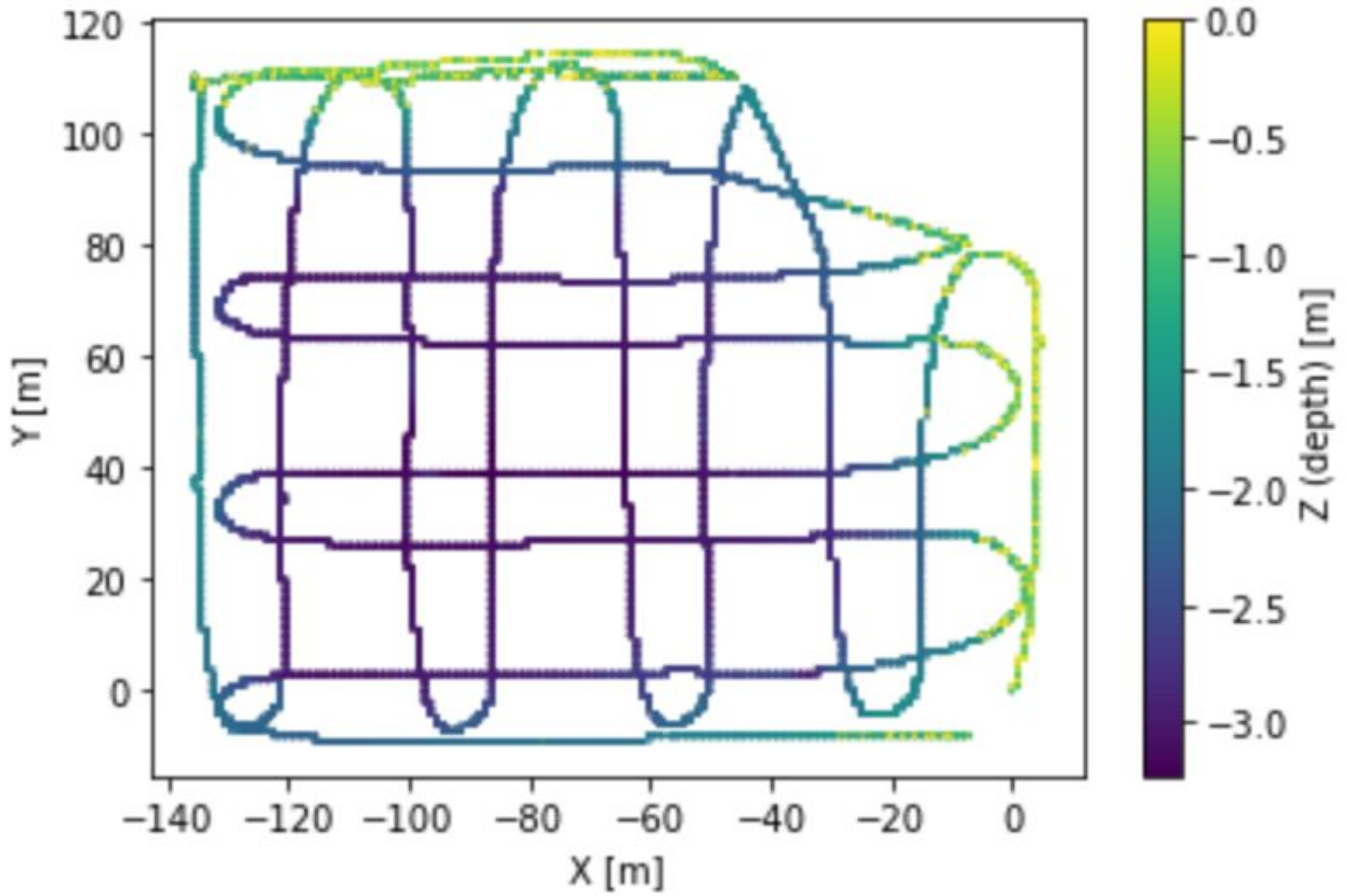
The Bathy-drone

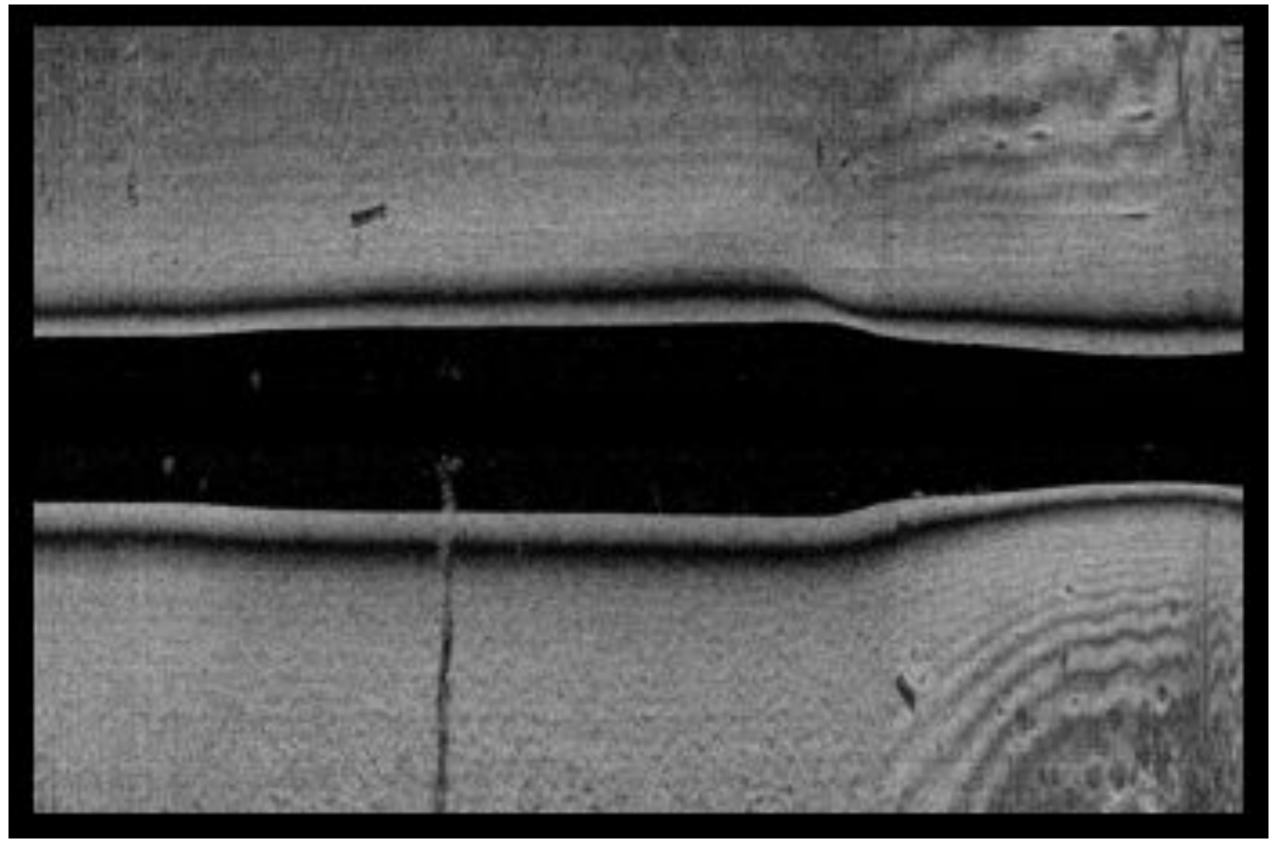
- Autonomous drone towing a tethered boat equipped with various sensors
- Can be flown to the survey location
- No propulsion system on boat
- Can traveling at speeds of 0-15 mph
- **The boat is equipped with a low-cost commercial off-the-shelf recreational fish-finder and a downscan sonar**

Problem Statement

Inputs: GPS location, downscan sonar depth, and side-scan sonar image

Goals: Map the bathymetry of a low-depth body of water in a quick manner and at the same time, identify and localize objects of interest





SPARSE POINT CLOUD GENERATION AND AUTOMATIC OBJECT DETECTION USING BATHY-DRONE

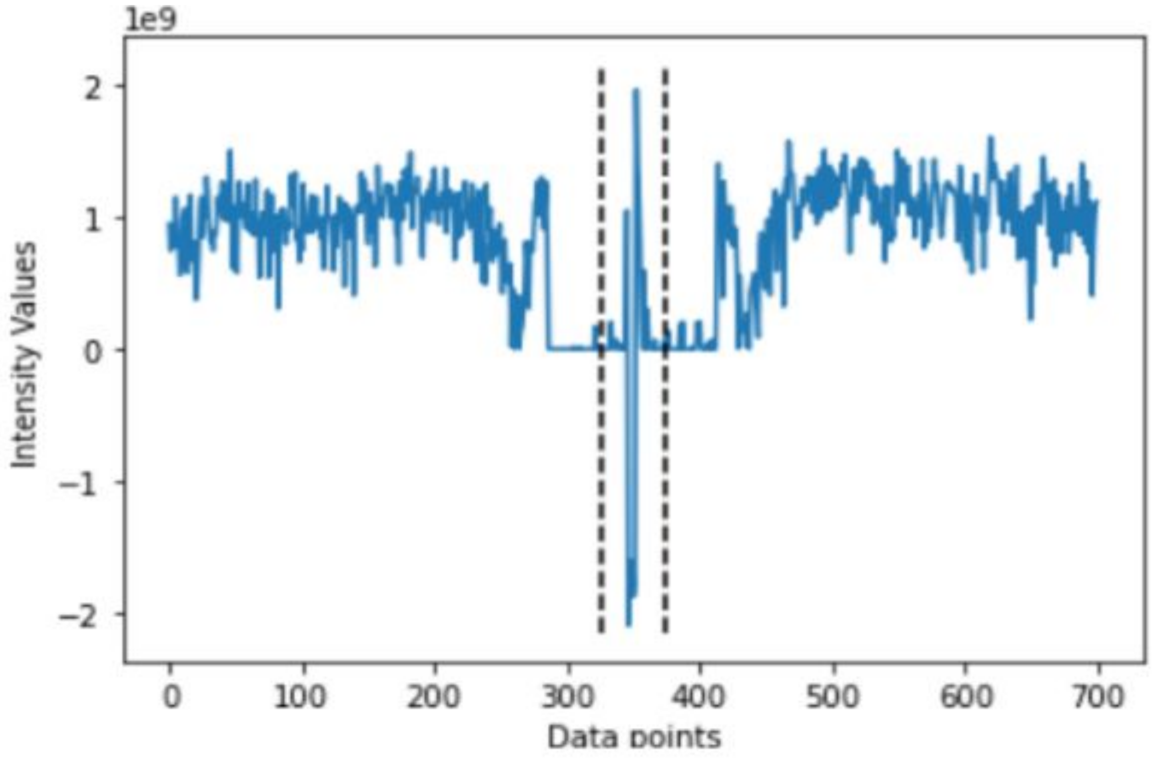
The algorithm consists of two stages:

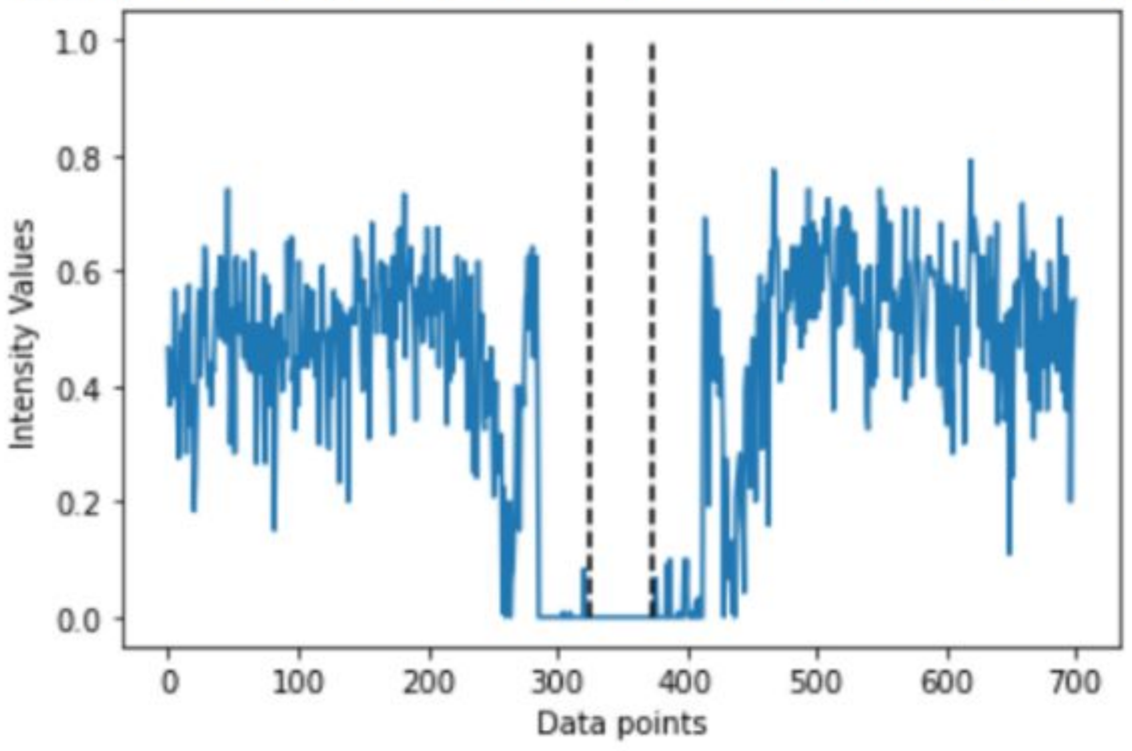
(1) Sparse point cloud generation
(2) Automatic object detection

SPARSE POINT CLOUD GENERATION

Image Normalization

The intensity is scaled to be in between 0 and 1 in order to be able to generalize to other sonar sensors





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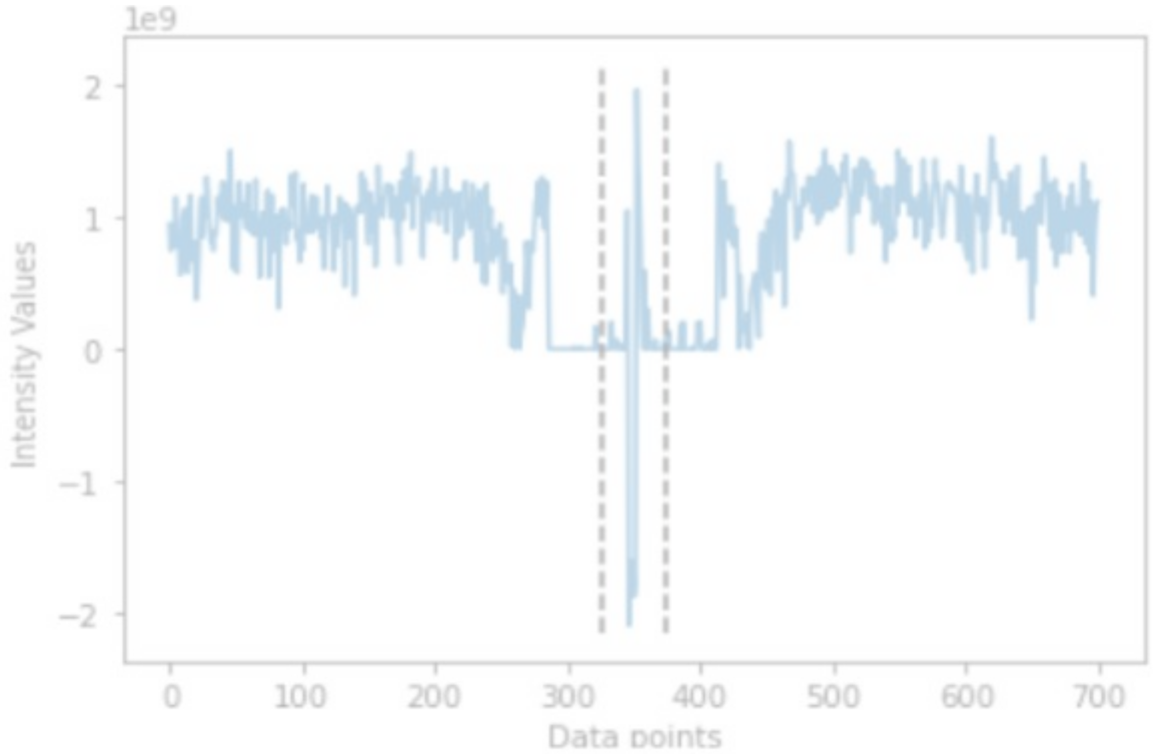
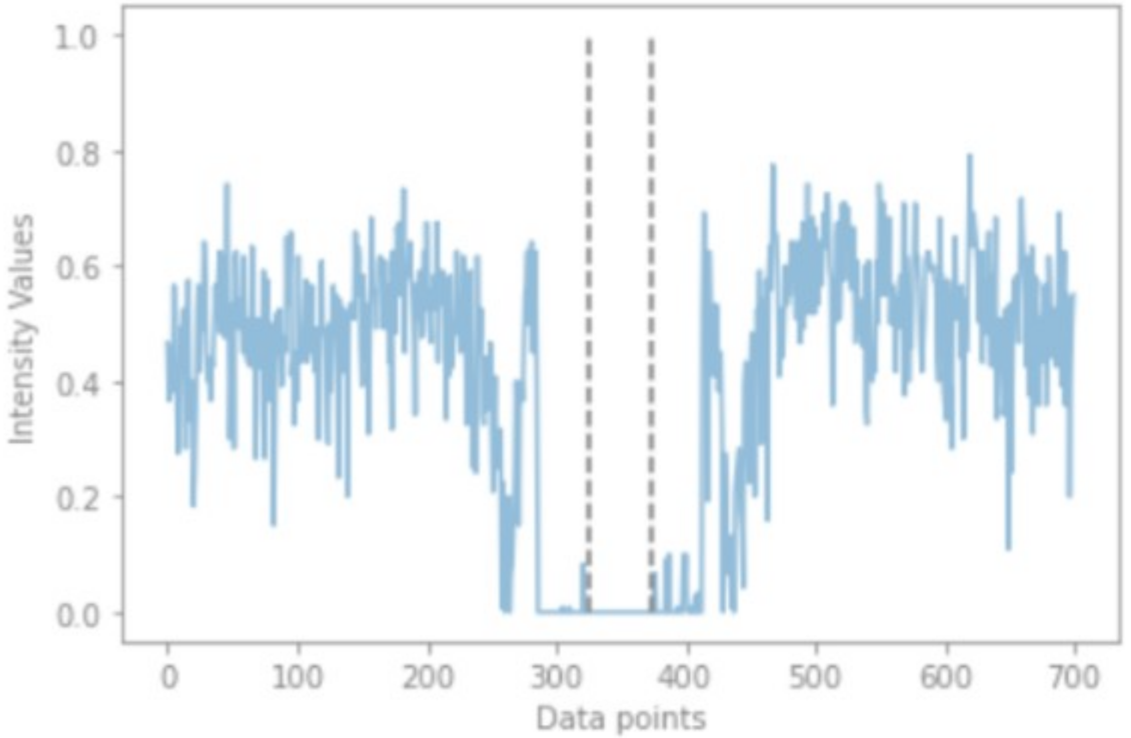
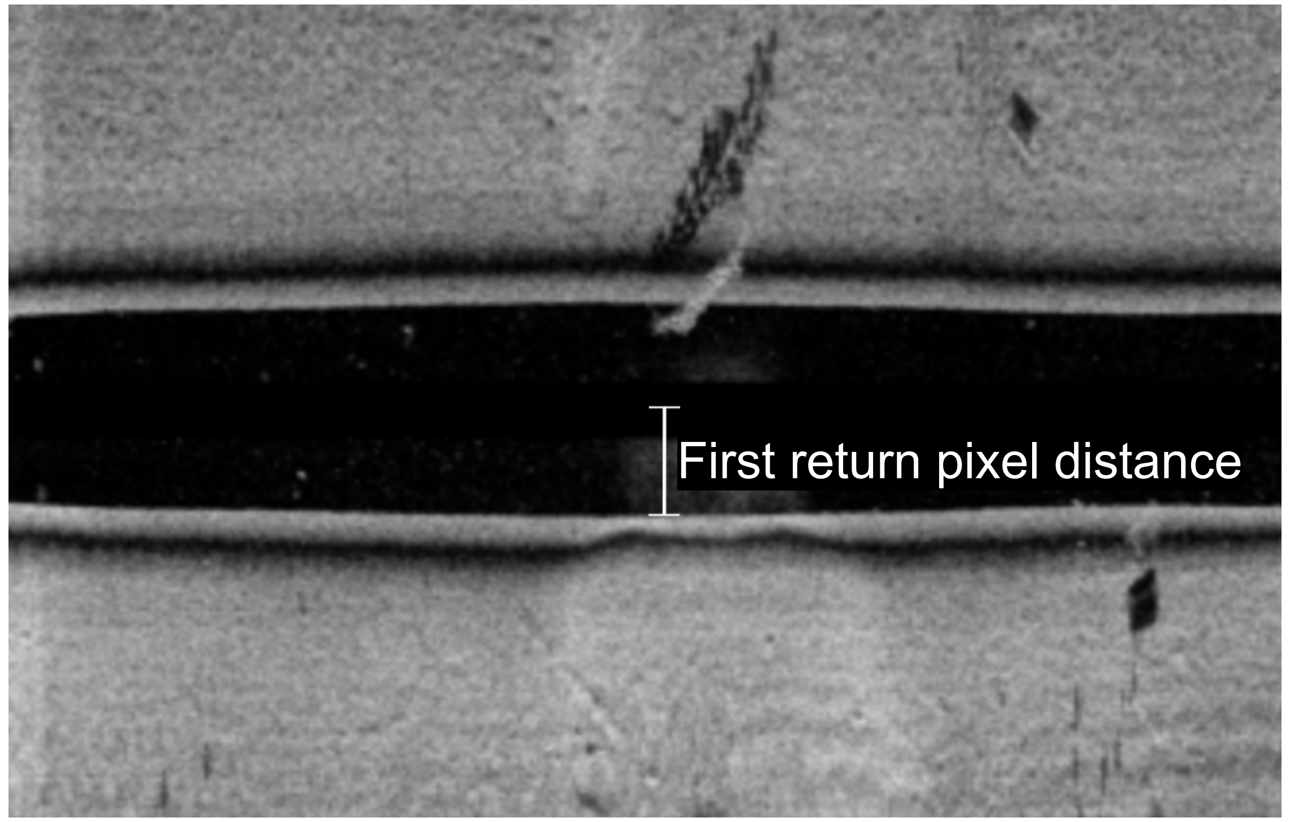




First Return

The first return is the first reading of the water floor from each sonar beam



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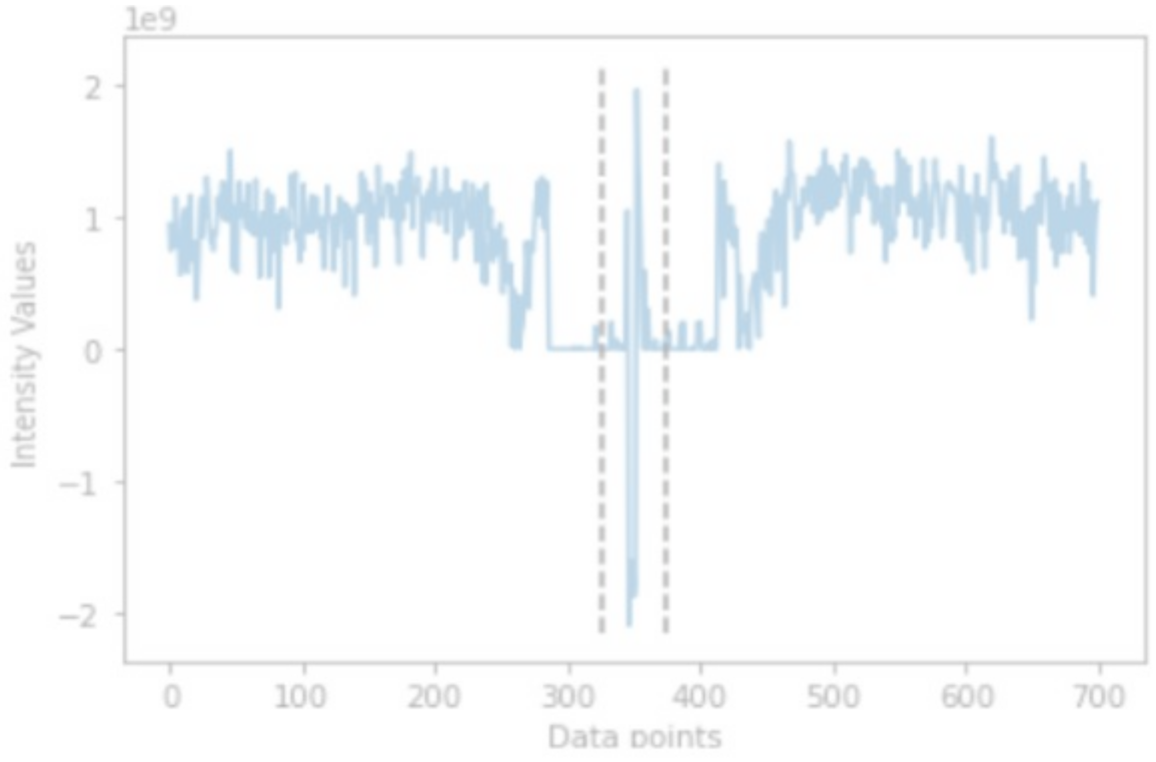

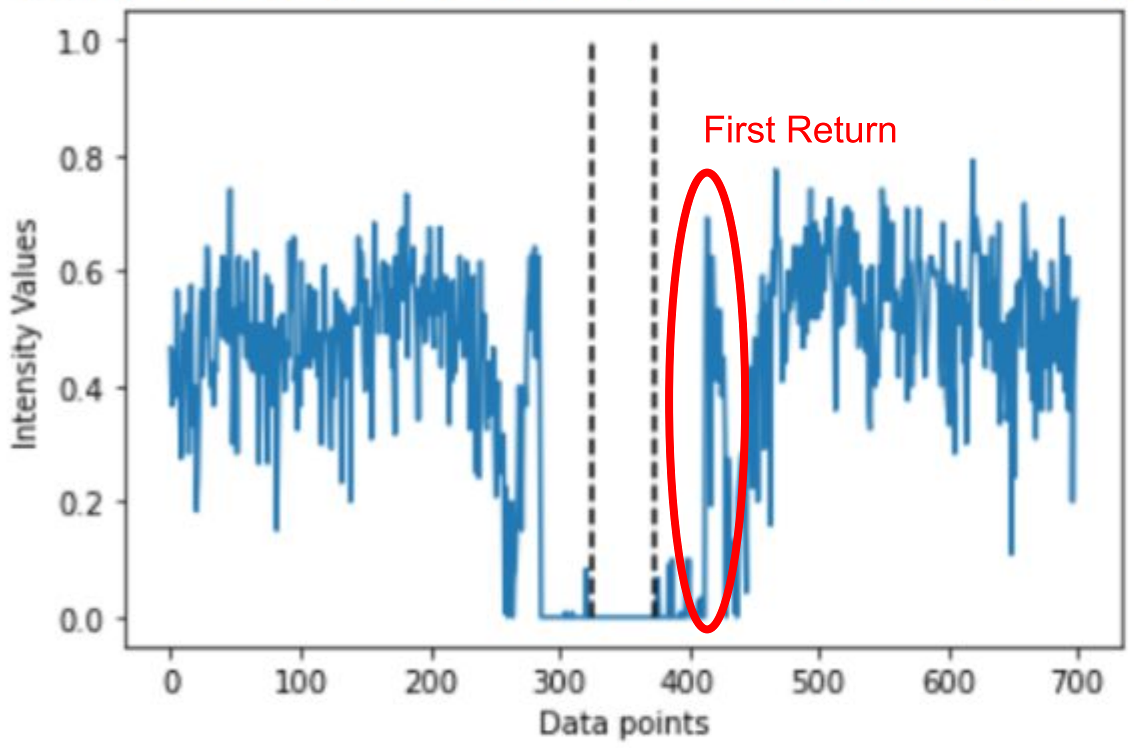

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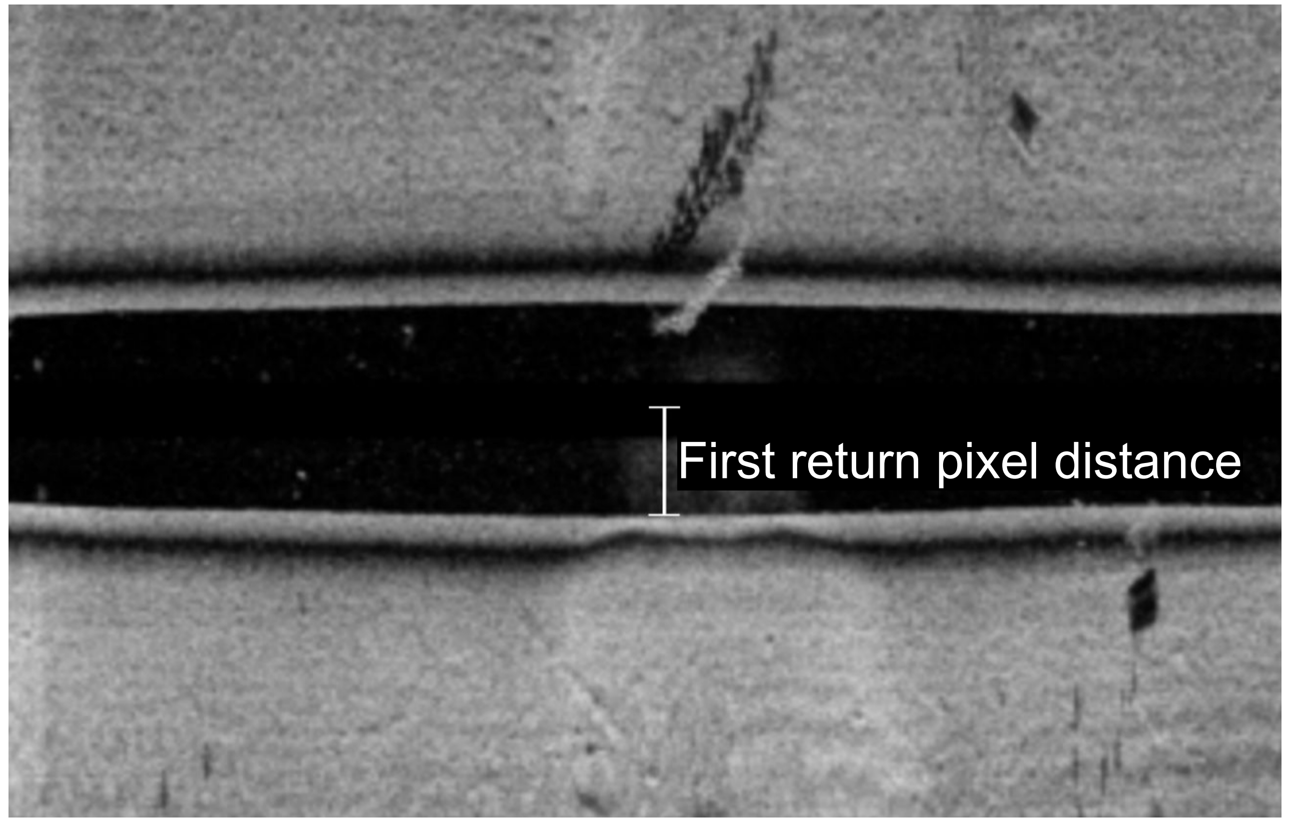
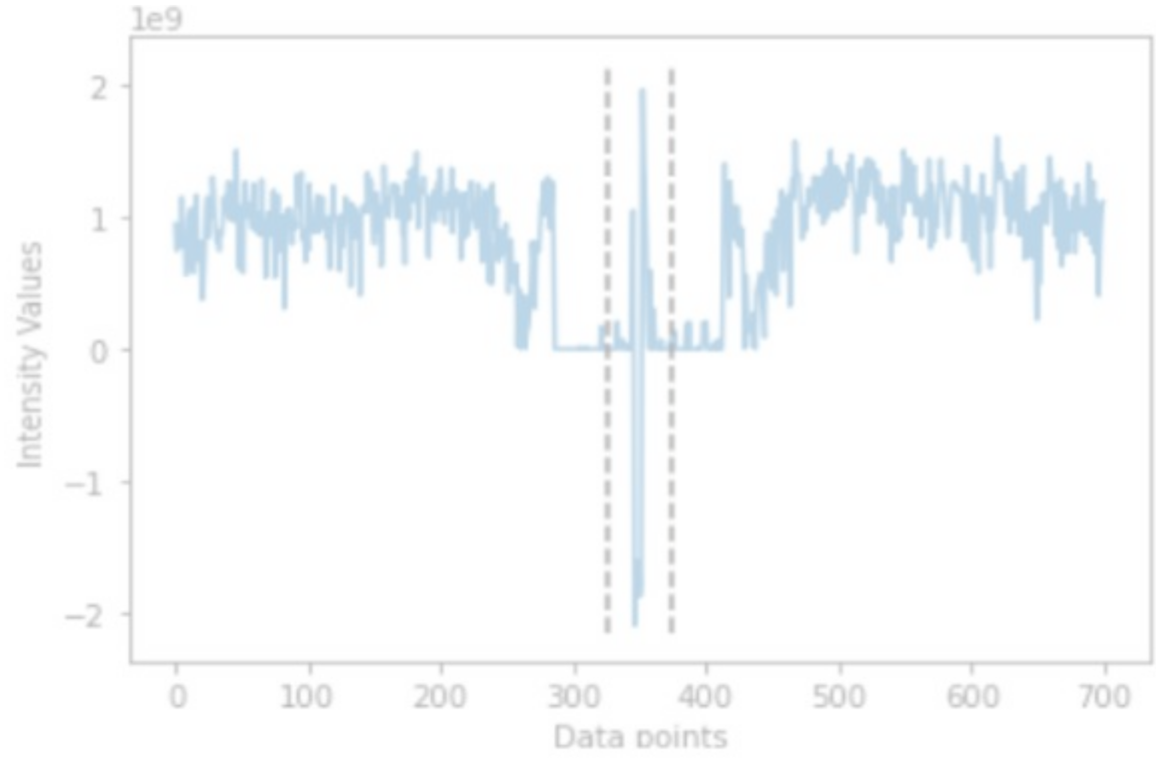
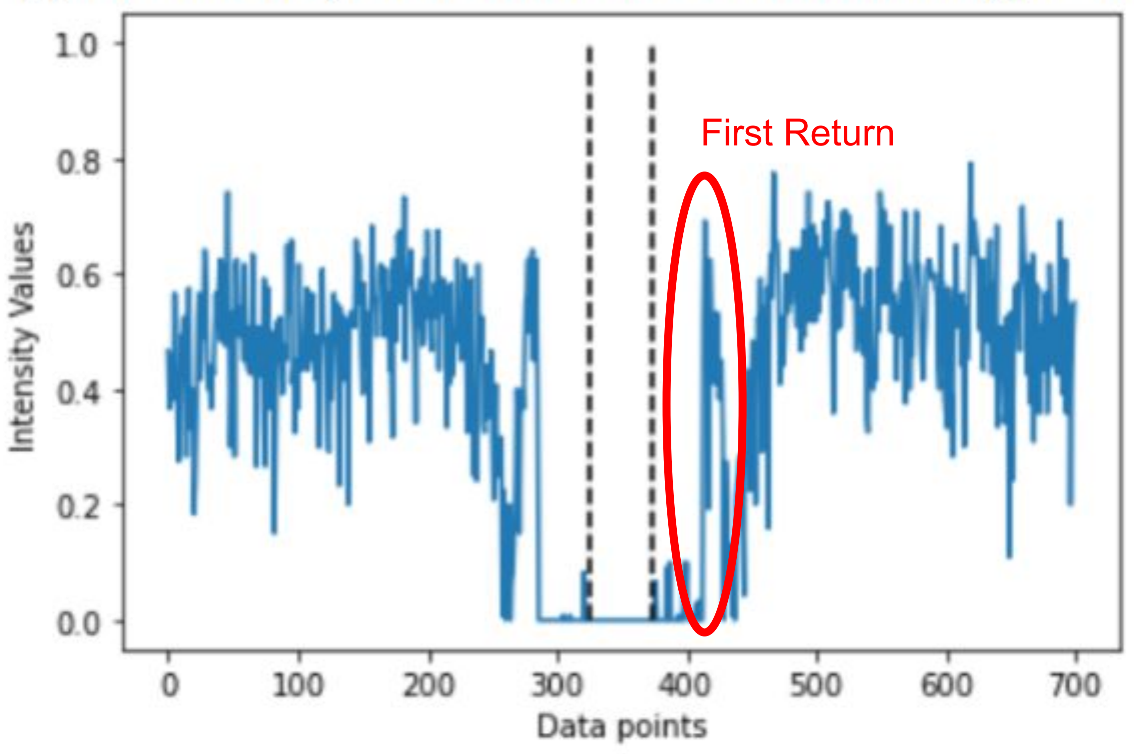
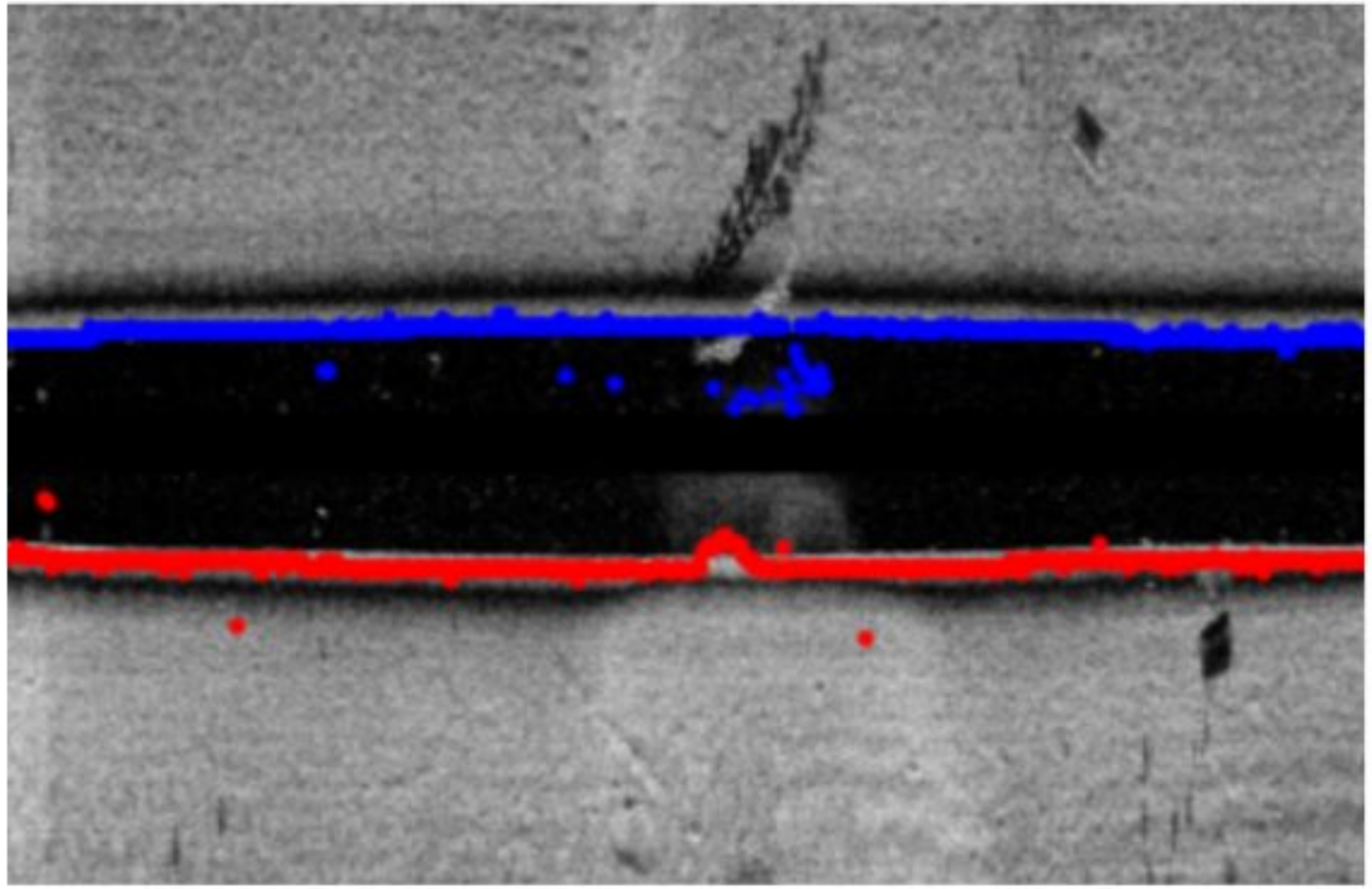


First Return

- Thresholding algorithm used to find the first return pixel
- Side-scan sonar image strip with the first return colored. Red (starboard) and blue (port)





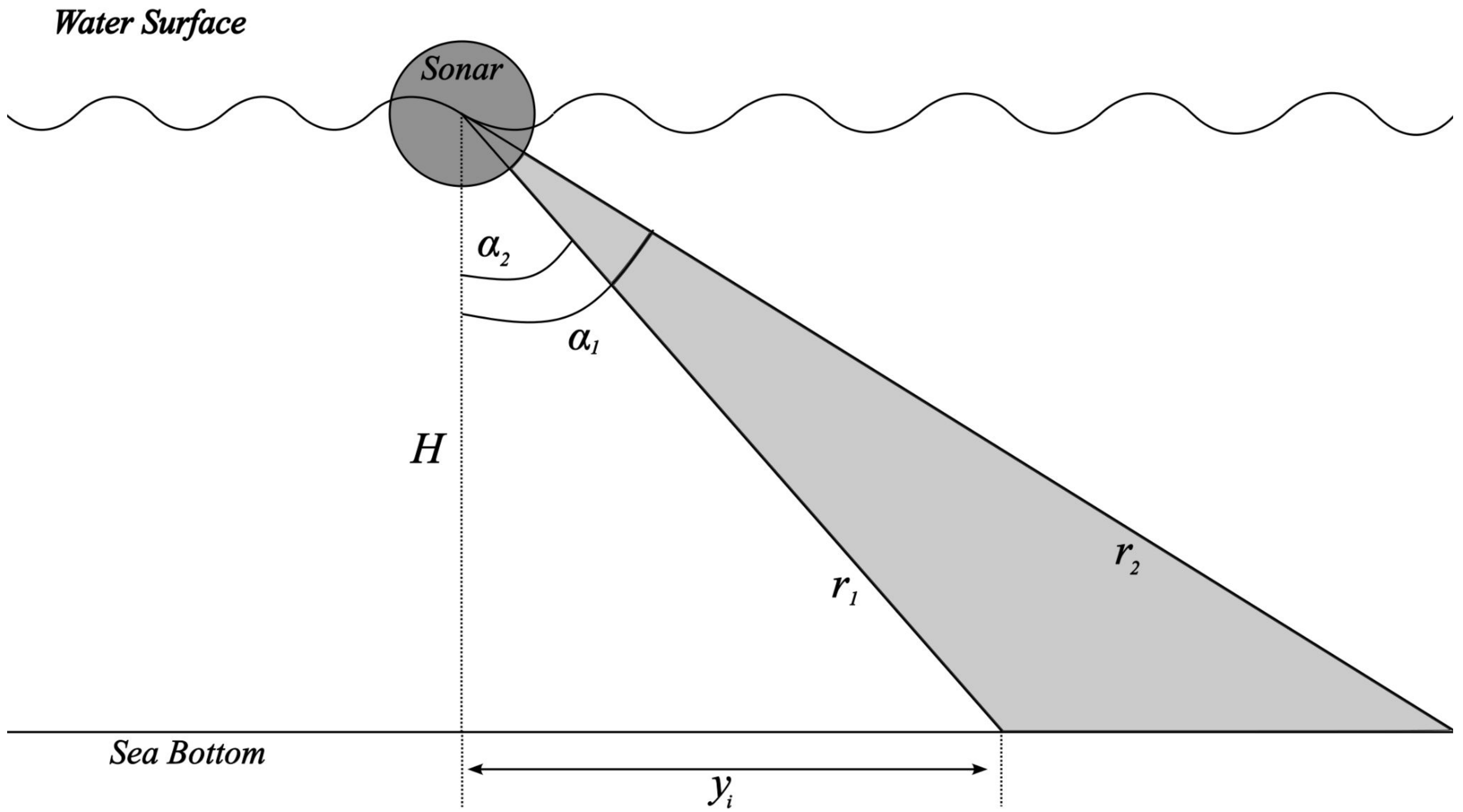


First return thresholding results

Side-scan Sonar Geometry

Depth and horizontal distance

$$z_i = r_{i,1}\cos(\alpha_2)$$
$$y_i = r_{i,1}\sin(\alpha_2)$$



$$PPD = \frac{(\text{pixels})}{(\text{distance})} = \frac{p}{d}$$

Linear mapping between distances and pixels

Pixel-distance Linear Mapping

Depth and horizontal distance

$$z_i = r_{i,1} \cos(\alpha_2)$$
$$y_i = r_{i,1} \sin(\alpha_2)$$

$$PPD = \frac{\text{(pixels)}}{\text{(distance)}} = \frac{p}{d}$$

Linear mapping between distances and pixels

Coordinate Transformation

Depth and horizontal distance

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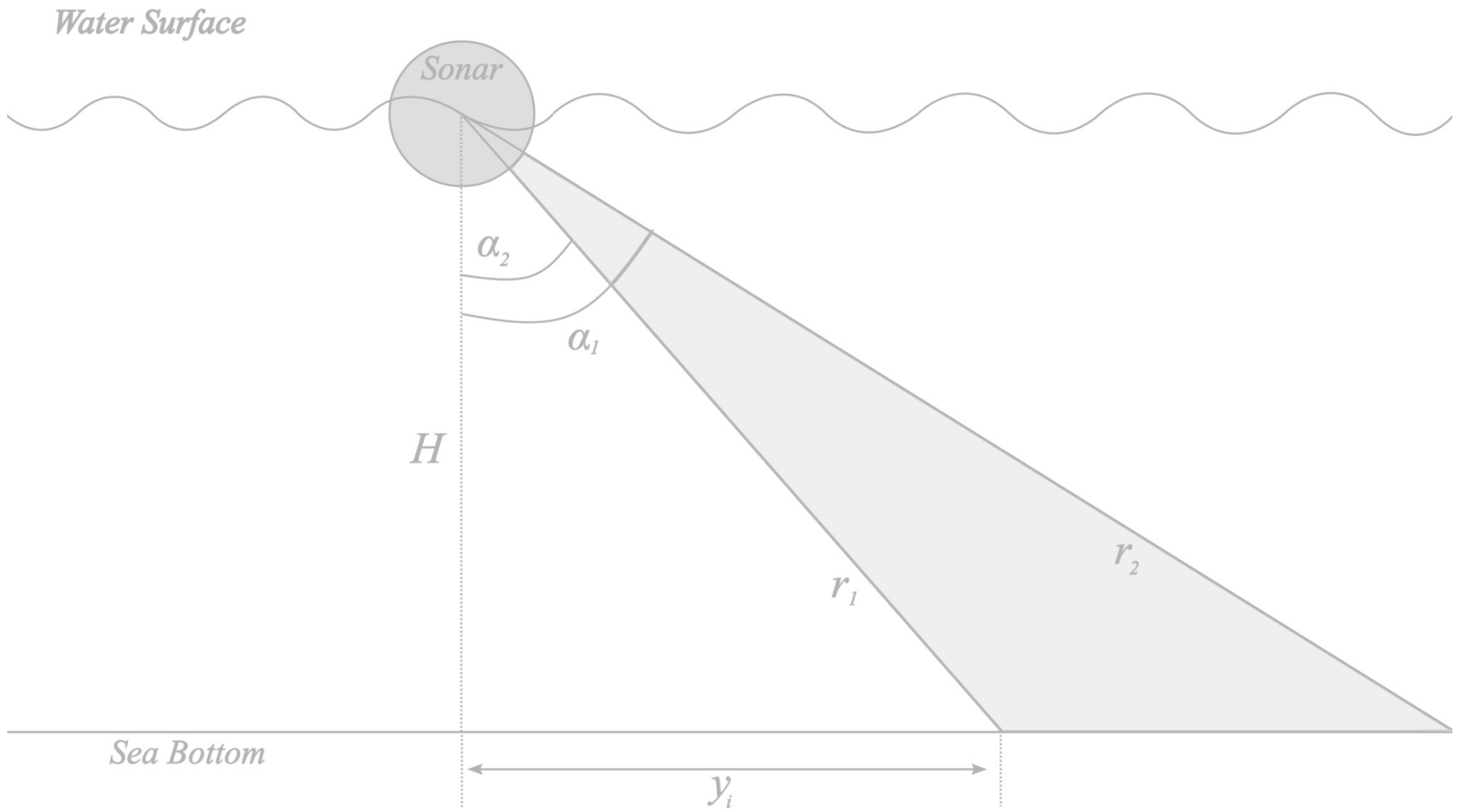

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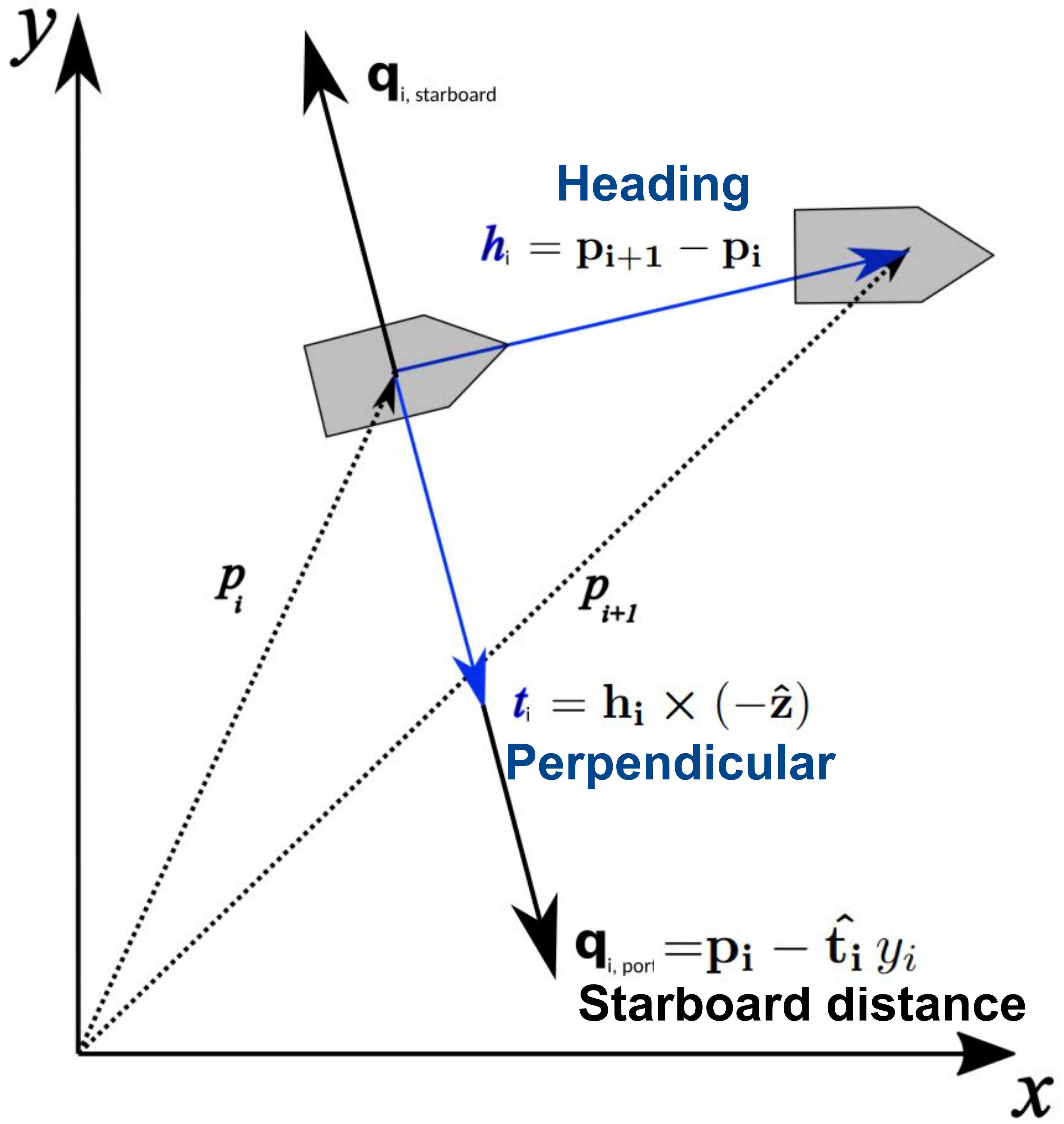

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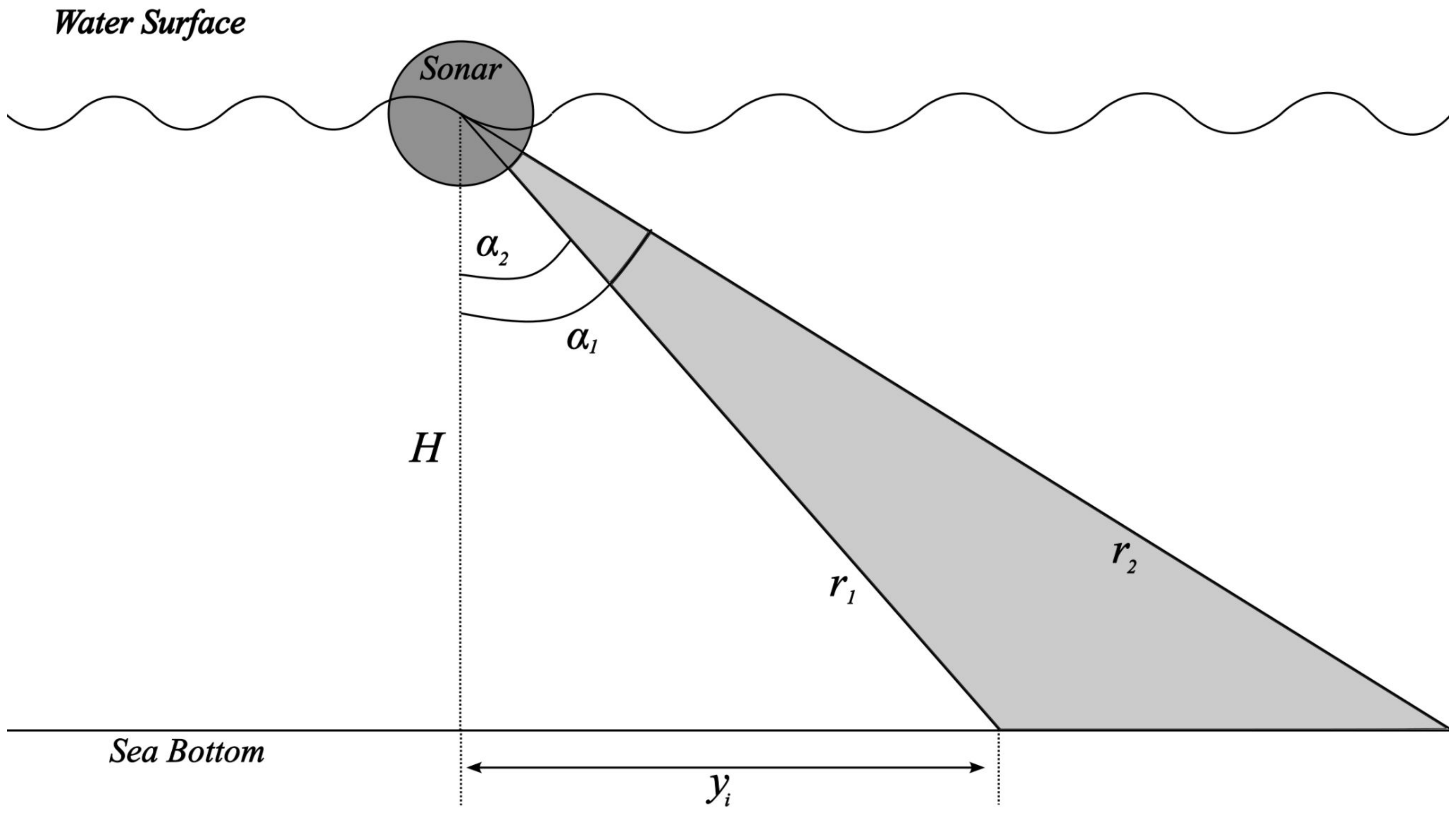

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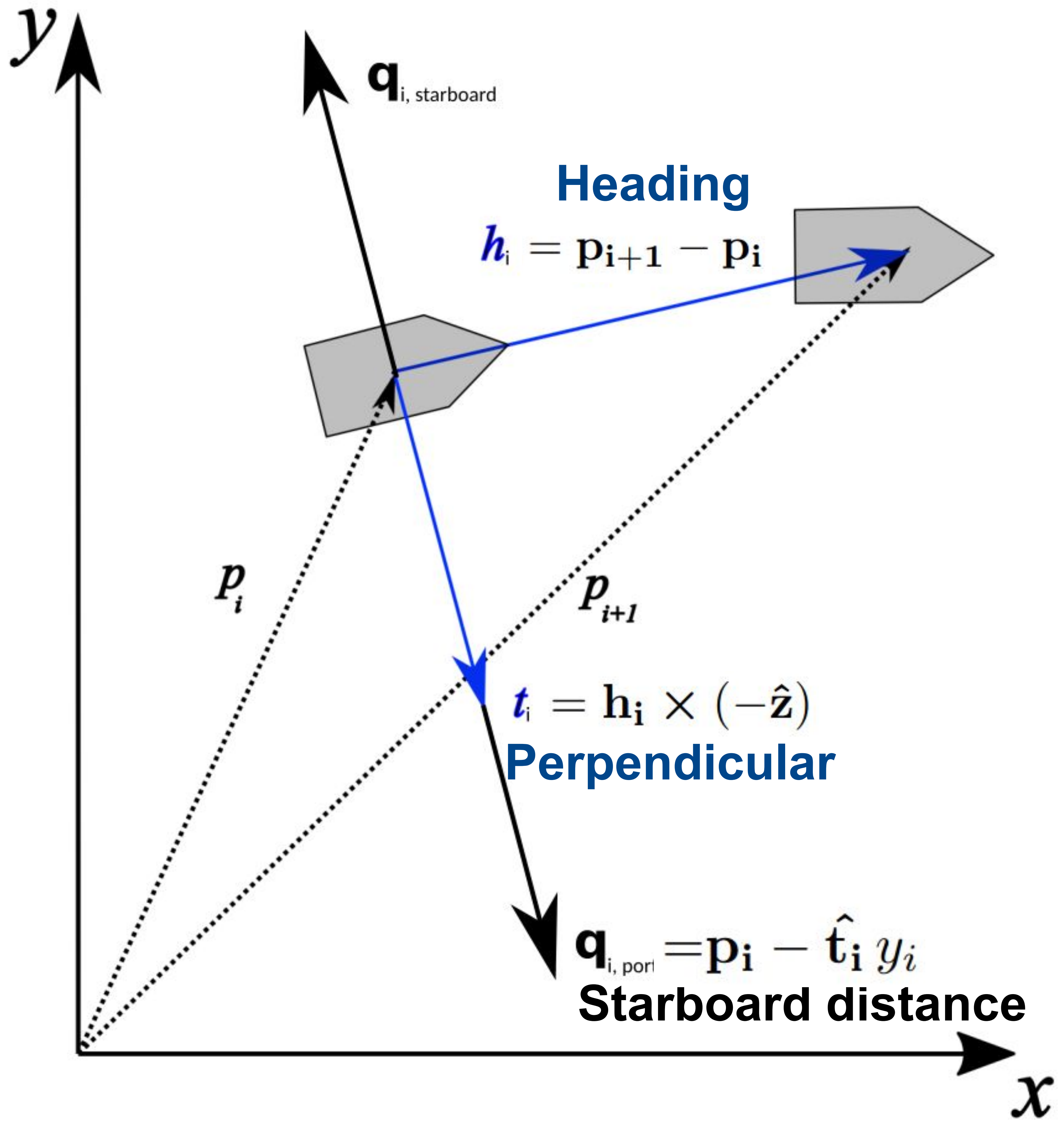
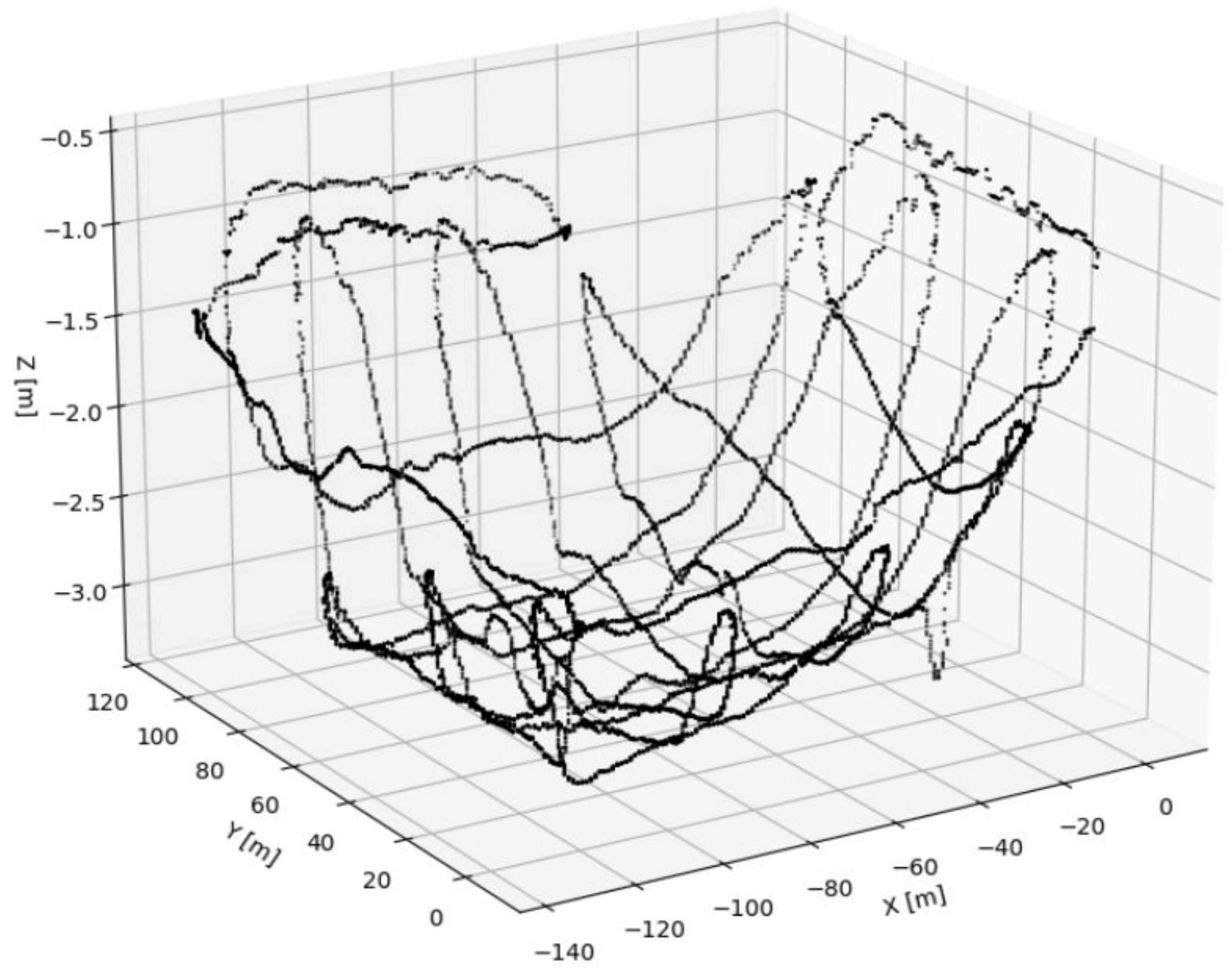
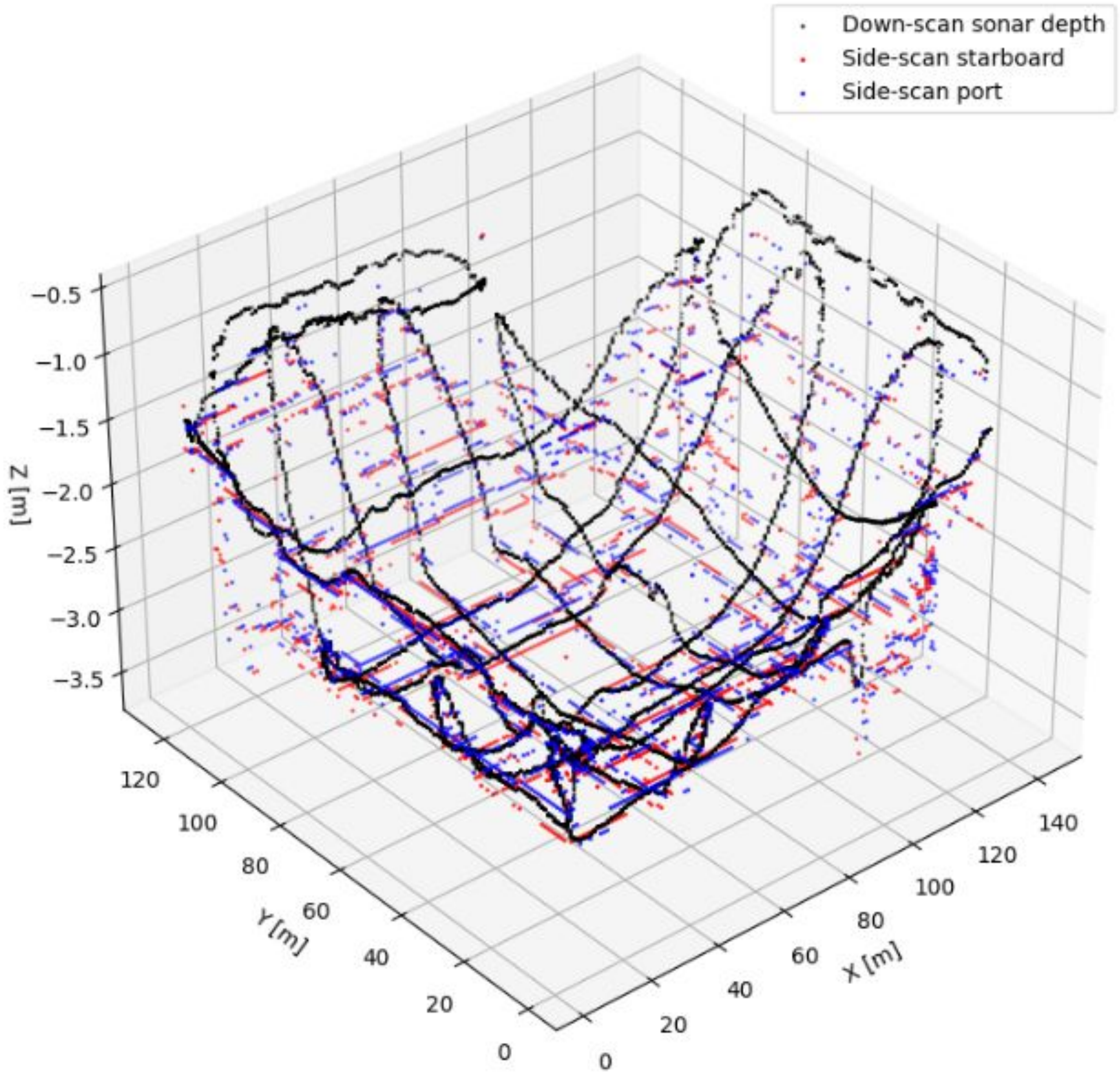


Sparse Point Cloud Generation Results



Point cloud data that are generated by down-scan and GPS data



Sparse Point cloud data that are generated by side-scan sonar return and geometry

AUTOMATIC OBJECT DETECTION

Automatic Object Detection Algorithm

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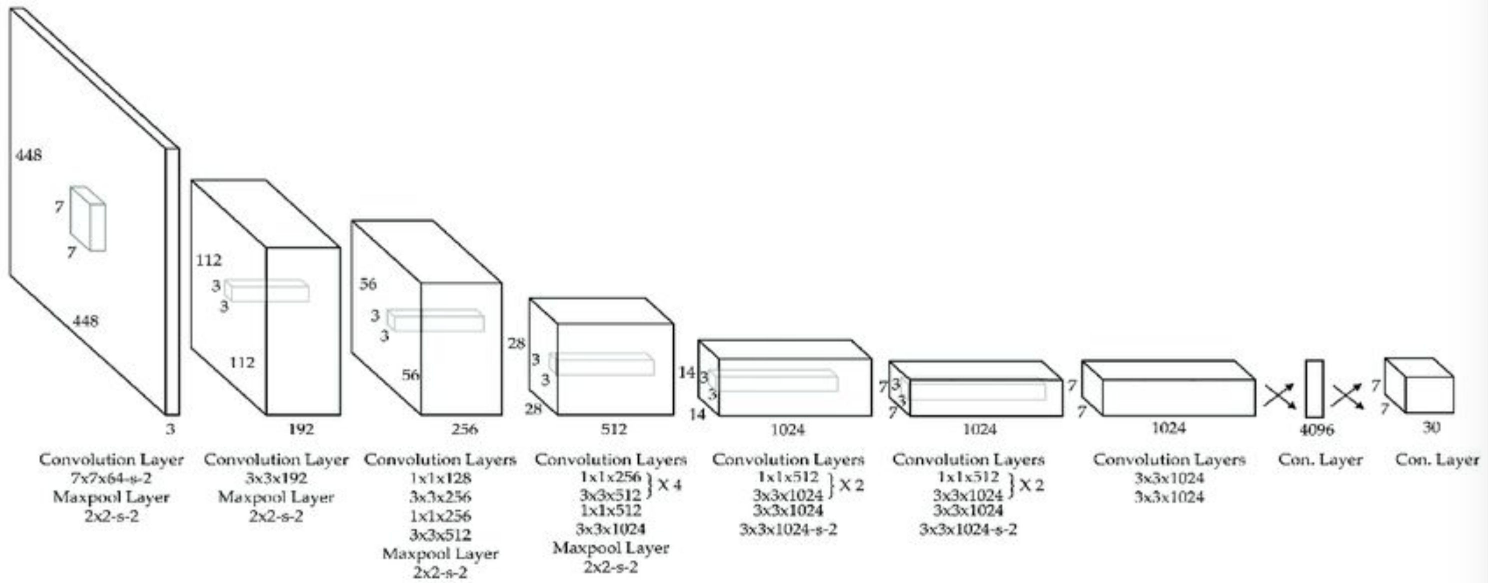
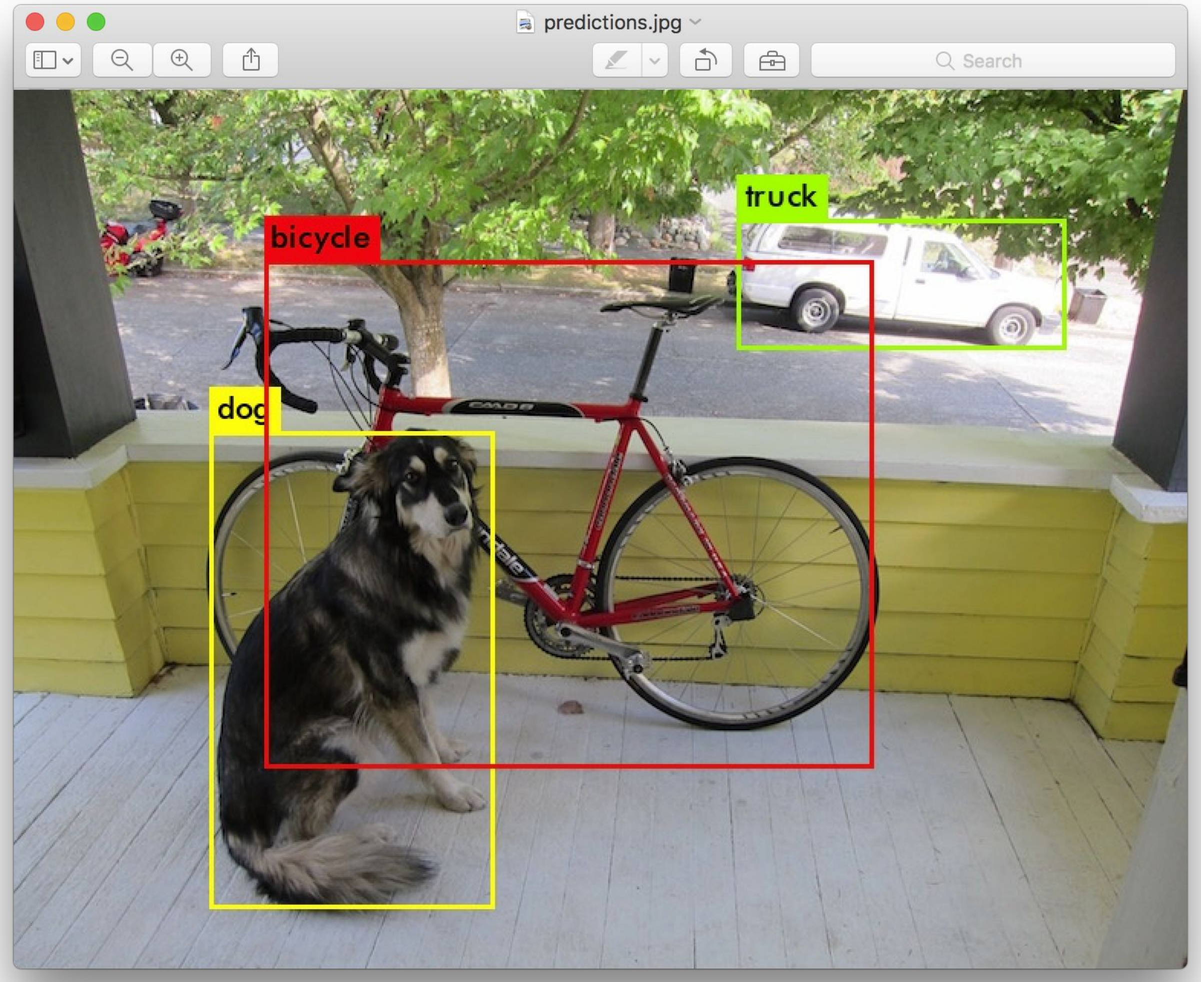
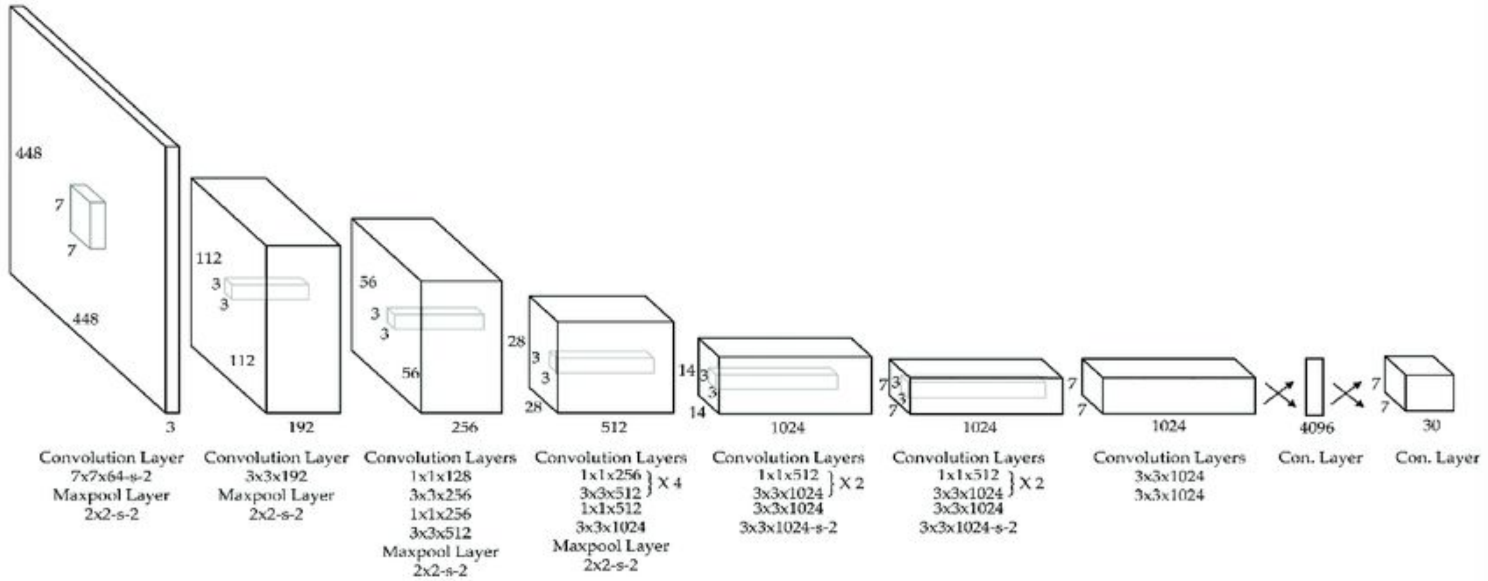




You Only Look Once
YOLO

Bounding Boxes

Automatic Object Detection Algorithm



Unreal Engine Synthetic Images → **You Only Look Once (YOLO Neural Network)** → **Bounding Boxes**

Evaluation of the Automatic Object Detection Algorithm

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Evaluation Metrics

Mean Average Precision:

How good it is at classifying

$$mAP = \frac{1}{N}\sum_{i=1}^{N} AP$$

Intersection Over Union:

How good is the localization of the bounding box

$$IoU = \frac{\text{(Area of Overlap)}}{\text{(Area of Union)}}$$

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Results

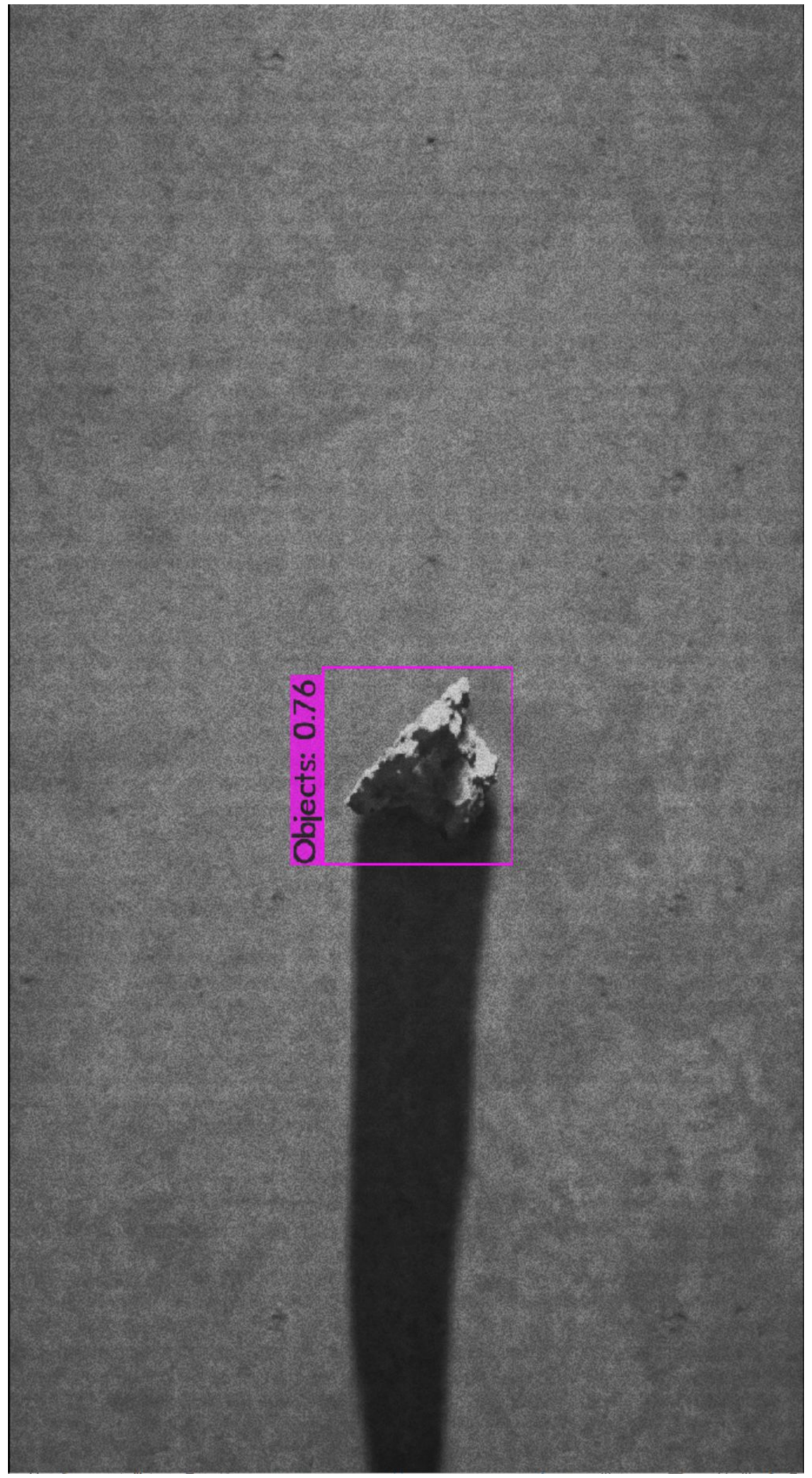
- 239 images in the training set (12 real)
- 59 images in the validation set (11 real)
- 45 images in the test set (2 real)

Table I: Metrics Result

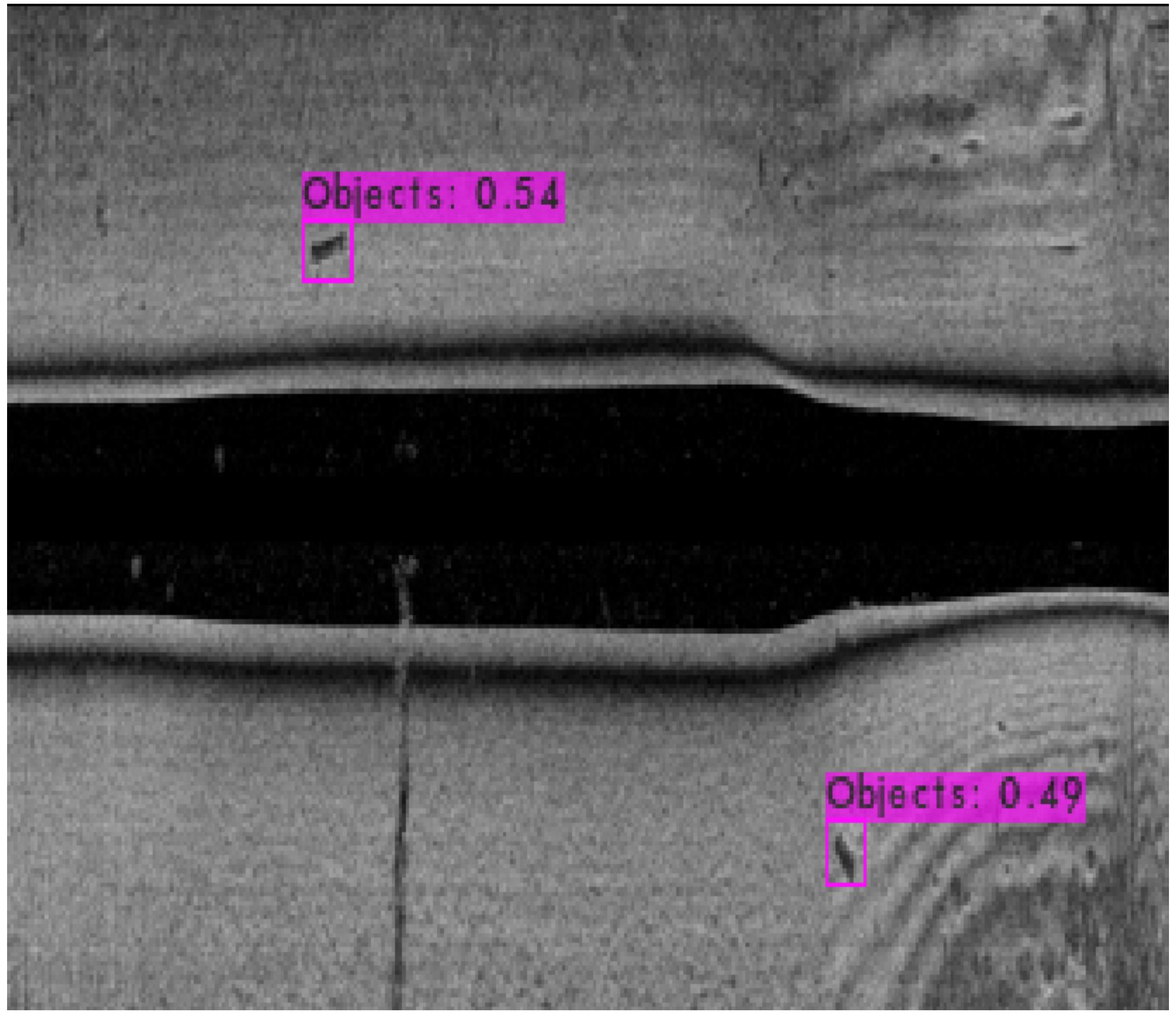
Metrics	Value
IoU	76.26%
mAP	93.17%

Object Detection Results

- Confidence level is high in synthetic images
- Confidence score drops in real images
- Drop could be mitigated by collecting more actual sonar images of objects with the sides-scan sonar



Synthetic Image



Real side-scan sonar image

References

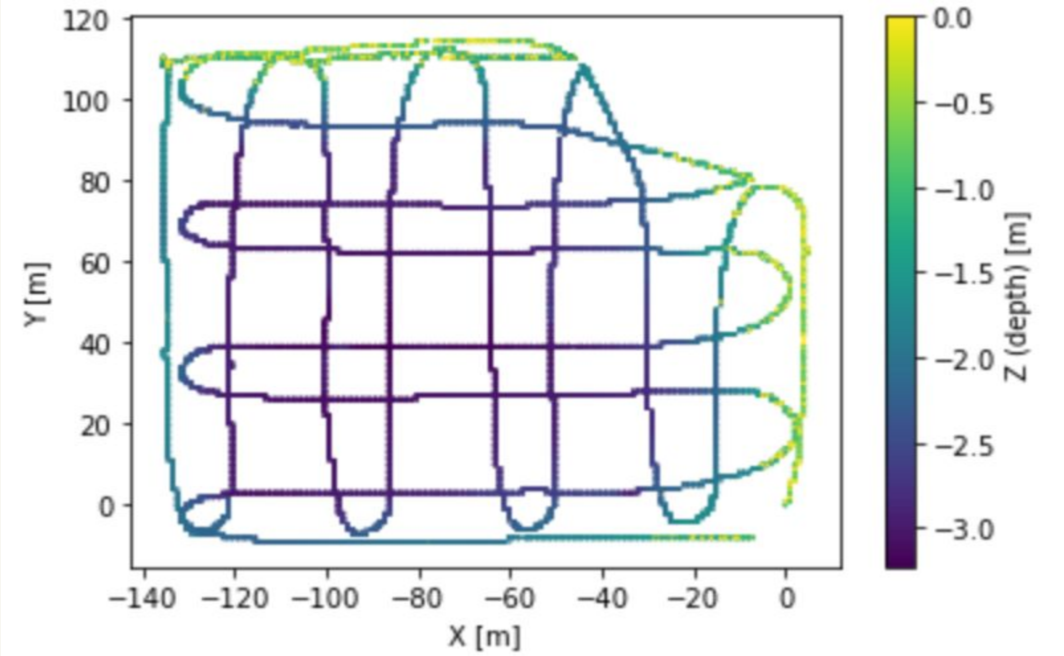
[1] Melo, José and Aníbal Matos. “Survey on advances on terrain based navigation for autonomous underwater vehicles.” Ocean Engineering 139 (2017): 250-264.

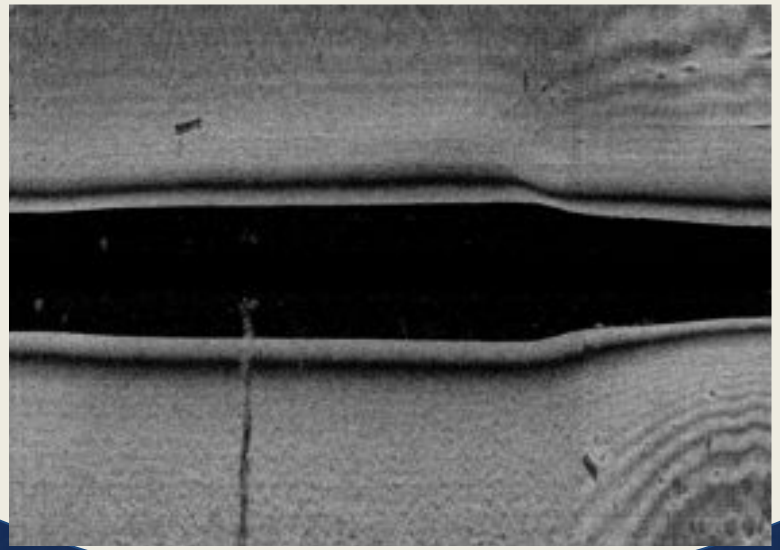
[2] K. Mizuno and A. Asada, “Three dimensional mapping of aquatic plants at shallow lakes using 1.8 MHz high-resolution acoustic imaging sonar and image processing technology,” in 2014 IEEE International Ultrasonics Sym-posium, pp. 1384–1387, ISSN: 1051-0117.

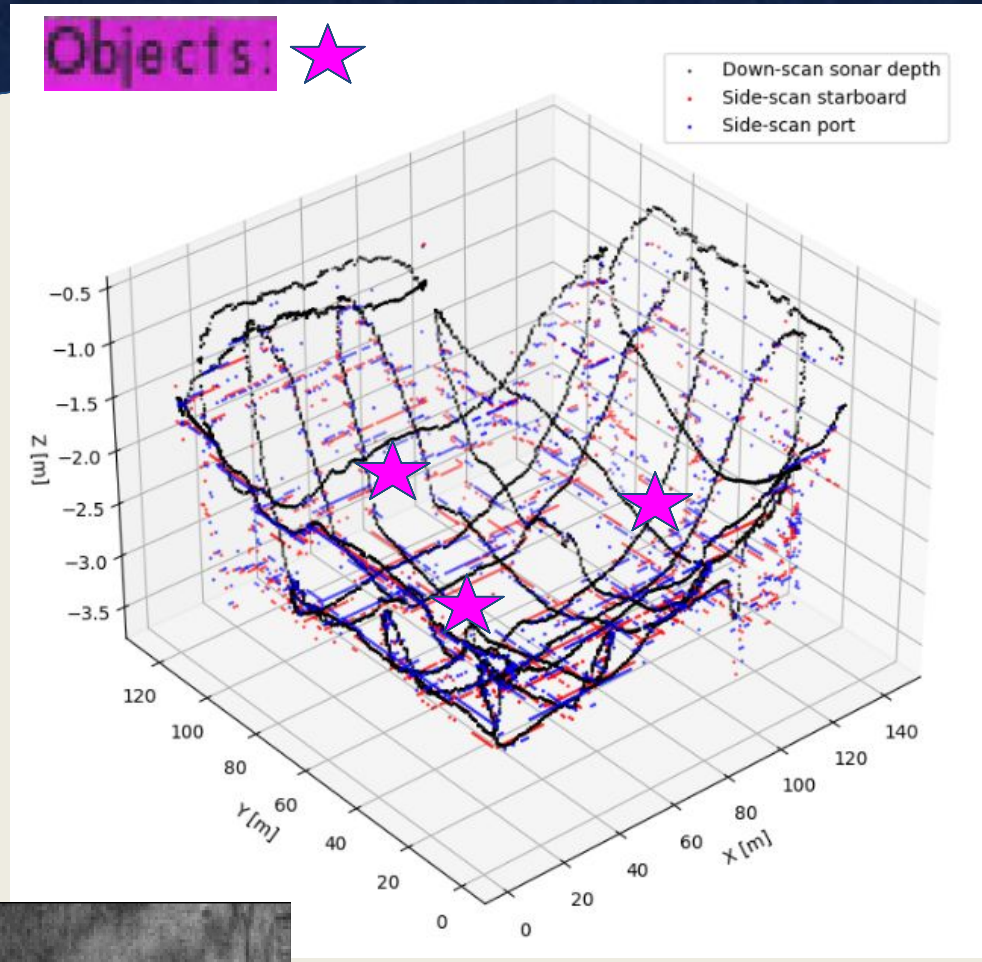
[3] T. Maki, H. Horimoto, T. Ishihara, and K. Kofuji, “Tracking a sea turtle by an AUV with a multibeam imaging sonar: Toward robotic observation of marine life,” vol. 18, no. 3, pp. 597–604.

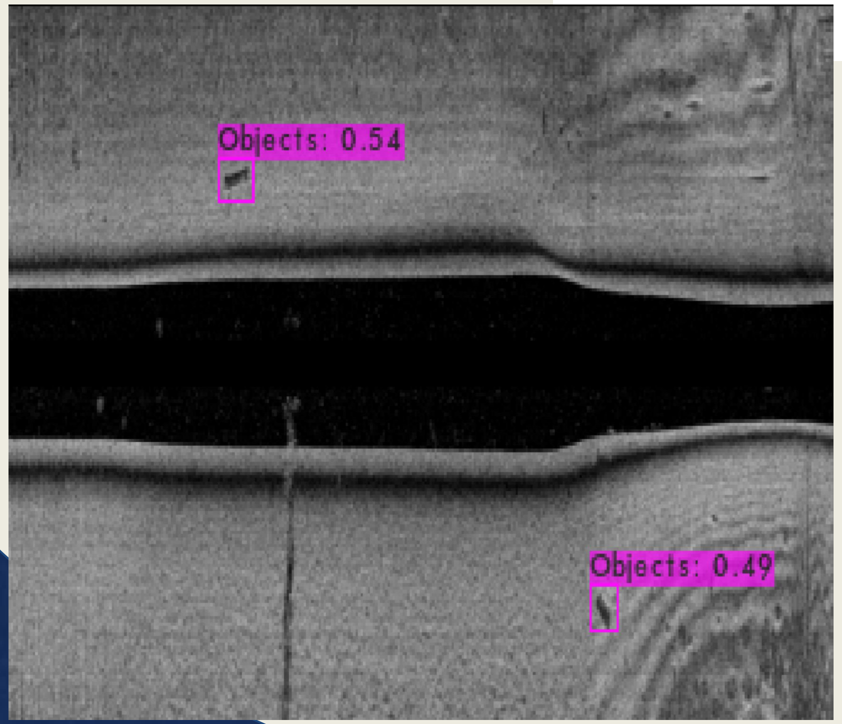
Thank you! Questions?

Sparse Point Cloud Algorithm and Automatic Object Detection









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