

SeePerSea: Multi-modal Perception Dataset of In-water Objects for Autonomous Surface Vehicles

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Abstract— This paper introduces the first publicly accessible labeled multi-modal perception dataset for autonomous maritime navigation, focusing on in-water obstacles within the aquatic environment to enhance situational awareness for Autonomous Surface Vehicles (ASVs). This dataset, collected over 4 years and consisting of diverse objects encountered under varying environmental conditions, aims to bridge the research gap in autonomous surface vehicles by providing a multi-modal, annotated, and ego-centric perception dataset, for object detection and classification. We also show the applicability of the proposed dataset by training deep learning-based open-source perception algorithms that have shown success. We expect that our dataset will contribute to development of the marine autonomy pipelines and marine (field) robotics. This dataset is opensource and can be found at <https://seepersea.github.io/>.

I. INTRODUCTION

Learning-based multi-modal algorithms have shown success in the terrestrial domain for self-driving cars on the road to autonomy. The precondition(s) to this success fundamentally rest on the availability of relevant labeled datasets [1]–[3]. Equivalent success in marine Autonomous Surface Vehicles (ASVs) has unsurprisingly been hampered by the lack of relevant multi-modal perception datasets. Thus, the goal of this paper is to **create the first multi-modal 3D perception dataset and make it publicly available for autonomous maritime navigation** (Fig. 1). This dataset, consisting of in-water obstacles in the aquatic domain, aims to enhance situational awareness for ASVs. Situational awareness is a foundational task that undergirds autonomy, which is increasing in importance given the focus on ASVs for tasks such as environmental monitoring and automated transportation. This importance will only grow as marine trade increases to 90% of the share of world trade [4] and the expected size of the ASV market will grow to 2.7B USD by 2032 [5]. Efforts by the International Maritime Organization

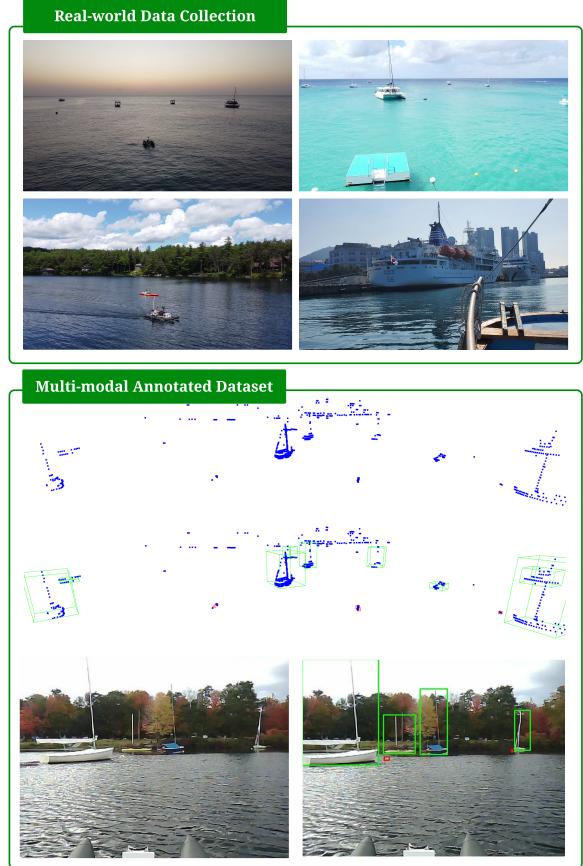


Fig. 1: Real-world data collection of in-water objects by ASV and human-driven boat in operation at different geographic locations and conditions. We provide multi-modal annotated dataset (LiDAR and RGB camera) for marine autonomy.

(IMO) under the United Nations (UN) further highlight the critical need for developing autonomous systems for the marine domain [6].

Understanding the locations of static and dynamic objects in the aquatic domain (**object detection**) and determining the types of these objects (**object classification**) are crucial tasks for *data association* to understand the speed and heading of approaching of risky objects. Such processes are ultimately useful for *navigational decision-making*, i.e., collision avoidance. However, aquatic domain's challenges including (1) unstructured navigational environments and (2) limited maneuverability of marine vehicles raise the importance of *early* and *accurate* state estimation of in-water

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TABLE I: Comparison of the state-of-the-art dataset in the maritime domain.

Dataset	Modality		Object Label	On-board Data	Area		Application	Sensors
	Image	Range			Coastal	Fresh		
MassMIND [7]	Y		Y	Y	Y	Y	Object Segmentation	IR cam
MaSTr1325, MODD [8]–[11]	Y		Y	Y	Y		Object Segmentation	RGB cam, IMU
VAIS [12]	Y		Y		Y		Object Classification	IR cam, RGB cam
MARVEL [13]	Y		Y		N/A*	N/A	Object Classification	RGB cam
SeaShips [14]	Y		Y		Y		Object Detection, Object Classification	RGB cam
WSODD [15]	Y		Y		Y	Y	Object Detection, Object Classification	RGB cam
USVInland [16]	Y	Y		Y		Y	SLAM, Water segmentation, Stereo matching	LiDAR, Stereo cam, RADAR, IMU
NTNU [17]	Y	Y		Y	Y		Object Tracking**	LiDAR, RADAR, EO and IR cam
Pohang [18]	Y	Y		Y	Y		SLAM	LiDAR, Stereo cam, AHRS, GPS, IR cam, RADAR
Ours	Y	Y	Y	Y	Y	Y	Object Detection, Object Classification	LiDAR, RGB cam, IMU, GPS

* The images contain ships but collected by data mining from web sources.

** The public data contains trajectories of detected vehicles, not the raw data of sensors.

obstacles for safe and efficient navigation against detection errors (e.g., false negatives). Among human error-driven marine accidents, over 70% is attributed to improper situational awareness [19]. Consequently, marine vehicles, even human-driven vessels, naturally rely on **multi-modal** data for situational awareness, which aligns with the regulations (e.g., rule 5 *look-out*) explicitly covered by the maritime Rules of the Road [20]. Effective cross-correlation of multi-modal data will be essential for robust maritime autonomy and will require high-quality, labeled, multi-modal datasets to enable capability creation as well as to validate performance.

Compared to the many existing labeled multi-modal terrestrial datasets for self-driving cars [1]–[3], there is a surprising lack of equivalent aquatic datasets for ASVs. This scarcity is mainly due to the high operational costs and the extensive effort required for labeling in the case of ASVs [7]. Among the few existing datasets in the aquatic domain, the open-source ones primarily consist of either (1) **single-modality** data that is typically image-based [9]–[15], [21], or (2) multiple modalities but lacking **object labels** across modalities [22], [23], which are essential for ground-truth evaluation [24]. This absence of multi-modal and ground-truth annotations significantly hinders the development of crucial ASV capabilities, as noted in [11], [24], such as perception and collision avoidance, which rely on supervised deep learning, and, by extension, labeled data-driven, approaches like those proven successful in other domains [25]–[28].

To address limitations (1) and (2), we release the first multi-modal labeled maritime dataset. Our dataset includes expeditions from 2021 to 2024 using our ASV platform *Catabot* and a human-driven vessel in different locations (United States, Barbados, and South Korea) covering various environments (both sea and fresh water), conditions (e.g., dusk, daylight), and encounters (e.g., head-on, crossing)

with various objects. Such heterogeneous data collections are essential to create representative feature sets and, by extension, generalizable algorithms. The proposed dataset includes navigation-oriented three classes (ship, buoy, and other) of labeled objects for detection and classification. We selected these labels according to the international traffic rule [20] and buoyage system [29]. In sum, the dataset is composed of 11,561 frames of LiDAR point clouds and RGB images. We also demonstrate the utility of the proposed dataset using deep learning-based open-source perception algorithms – both single-modality and fusion – that have shown success in the terrestrial domain, with both quantitative and qualitative evaluations: highlighting success in some scenarios, but also current gaps. We release our dataset publicly (<https://seepersea.github.io/>) for the community and expect it will have the following contributions:

- SeePerSea, being the first LiDAR-camera dataset in aquatic environments with object labels across the two modalities, will foster the development of robust fusion perception pipelines for ASV autonomy.
- SeePerSea, covering various environments and day conditions, will help ensuring that the developed perception pipelines are generalizable.

Overall, the SeePerSea dataset will contribute to the development of state-of-the-art marine autonomy pipelines and accelerate the future of marine (field) robotics.

The structure of this paper is as follows. Section II discusses datasets both in the ground and maritime domain. Section III describes how the data was collected, annotated, and structured. Section IV provides an analysis of the dataset characteristic. Section V presents the results from current deep learning pipelines trained on the provided dataset and Section VI discusses lessons learned and current gaps. Finally, Section VII summarizes the paper and highlights

future work.

II. RELATED WORK

Self-driving car datasets focused on 3D perception, including [1]–[3], have been crucial for progress in terrestrial robotic perception, especially for tasks like object detection, classification, segmentation, and tracking. These collections frequently feature a range of sensors, employing either individual or combined data from cameras, LiDAR, and RADAR. Given the importance of these datasets, there is a push to develop specialized datasets for the marine domain to support the advancement of marine autonomy.

Maritime object detection and classification datasets mainly consist of a **single sensor modality**, i.e., camera sensors, used for different purposes. Key datasets include the first visible and infrared ship image dataset for autonomous navigation compliance [12], a large-scale maritime dataset with over 2 million images detailing vessel information from a community site [13], and a dataset of common ship types from coastal surveillance [14]. [15] introduced more variety with different water surface objects. However, most datasets were from stationary platforms, not from an **ego-centric perspective**. A significant onboard camera dataset exists [21] but is not public. Public datasets [8]–[11] consist of several annotated videos collected by a real ASV platform, but these primarily focus on object segmentation with four classes – sea (water), sky, environment, obstacle – lacking differentiation of in-water objects like buoys and ships. [7] presents a Long Wave Infrared (LWIR) dataset with categories including sky, water, obstacle, but still limited to a **single modality**.

Several **multi-modal** datasets [16]–[18] are available, targeting different aspects of marine perception but not directly focusing on **object detection** and **classification**. [16] covers inland waterway scenes using LiDAR, stereo cameras, RADAR, GPS, and IMUs, for water segmentation, SLAM, and stereo matching. [17] combines data from 10 cameras, RADAR, and LiDAR for object tracking. [18] collects data from a diverse set of sensors over a 7.5 km route, aiming at SLAM and docking. Table I provides an overview of the discussed datasets compared to ours. This lack of datasets in the marine domain, specifically missing the key situational awareness tasks previously described, hampers progress in marine autonomy .

III. DATASET GENERATION

A. Sensor Configurations

As shown in Fig. 2, we used our custom ASV *Catabot* (in three different configurations) and a human-driven boat installed with a sensor platform. The different configurations allowed to collect diverse data that includes different vehicle dynamics. The *Catabot* dimensions range from 1.08 m to 2.68 m long, and from 1.40 m to 1.67 m wide. The human-driven boat is 8.27 m long, 2.34 m wide. Both include a Global Positioning System (GPS) / Compass and Inertial

Measurement Unit (IMU) with a flight controller unit, installed at the center line of the vehicle, to record proprioceptive data. We used a low-cost u-blox M8N GPS/Compass module. The flight controller hardware we used was a *Pixhawk 4* coupled with a 32-Bit Arm Cortex-M7 microcontroller with a 216 MHz clock speed and 2 MB of flash memory and 512 kB of RAM.

For exteroceptive data, we installed a RGB camera (Full-HD 1080P with CMOS OV2710 image sensor that can support Infrared (IR) during the nighttime) and a 64 channel LiDAR (Ouster OS1-64 gen2). The two exteroceptive sensors were located at the center line of the vehicles to ensure a sufficient horizontal field of view (Camera – 91.8°; LiDAR – 360° except for the blind sector due to occlusion caused by the vehicle structure) and vertical field of view (Camera – 75.5°; LiDAR – 45°). The LiDAR has a range of 120 m with a horizontal resolution of 0.35° and vertical resolution of 0.7°, while the camera sensor has a 640 × 480 pixel resolution.

We performed intrinsic calibration of each sensor and an extrinsic calibration between camera and LiDAR based on [30], [31]. We provide a custom tool for checking the extrinsic calibration parameters and overlay of multi-modal data as shown in Fig. 3a. We report the result of the calibration parameters per each sequence of the dataset.

B. Data Collection and Processing

We used a companion computer system (Intel NUC) and recorded proprioceptive (GPS, Compass, IMU) and exteroceptive (RGB camera, LiDAR) data via the Robot Operating System (ROS). Our Intel NUC computer with Ubuntu 18.04 installed has an Intel Core i7-8559U Processor (8M Cache, up to 4.50 GHz) with 1 TB of storage. The heterogeneous sensors operate at different time frequencies: we used a camera with a frequency of 30 Hz and LiDAR with a frequency of 10 Hz.

We collected relevant data in *{sea,fresh}* waters with varying environmental conditions *{dusk,day,night}*. We controlled the ASV via either (1) autonomous waypoint following or (2) manual driving, while we manually navigated the human-driven boat. Fig. 4 shows the trajectories during data collection. Our dataset covers collections conducted between 2021 to 2024 in different geographic locations: Lake Sunapee, NH, USA; Lake Mascoma, NH, USA; Busan Port, South Korea; Holetown, Barbados.

We post-process the camera and LiDAR data by extracting raw images and point clouds under time synchronization using the *MessageFilter* package [32].

C. Groundtruth Generation

We provide annotations of three in-water object classes based on the domain knowledge and navigation-oriented categorization: **ship**, **buoy**, and **other**, within the camera’s field of view as well as the LiDAR’s field of view (FoV). More specifically, (1) the **ship class** represents all marine vehicles defined according to the international traffic rule [20] as “every description of watercraft used or capable

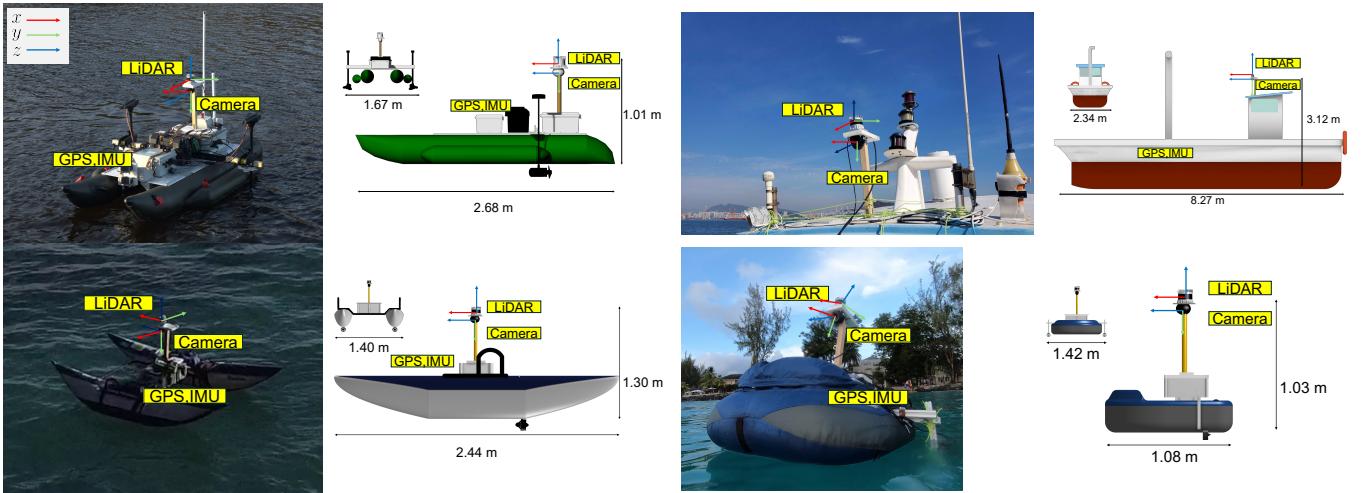


Fig. 2: Data collection platform (*top left*): our custom ASV *Catabot2*, (*top right*): human-driven ship equipped with sensors, (*bottom left*): our custom ASV *Catabot1*, (*bottom right*): our custom ASV *Catabot5*.

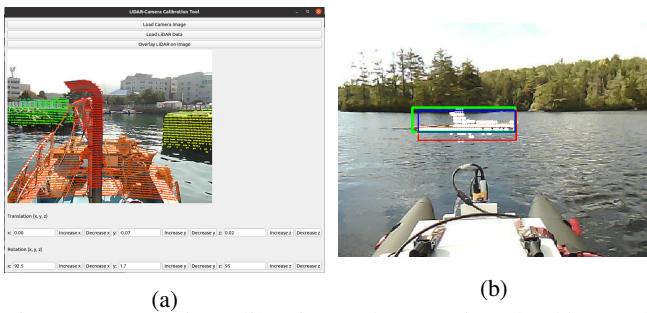


Fig. 3: Sensor suite calibration and annotation checking tool. (a) LiDAR and camera extrinsic calibration; and (b) a point cloud (white) overlaid on the corresponding RGB image to check consistency over labels (green: image label, red: point cloud label, blue: intersection).

of being used as a means of transportation on water”, including examples such as power-driven vessels, fishing boats, kayaks, yachts, sailboats; (2) the **buoy class** represents floating objects as defined by the International Maritime Buoyage System [29] and includes any artificial objects serving as “aids to navigation”, like cardinal, lateral, safe water, isolated danger, and special buoys with varying colors and shapes, such as ball and pillar types; and (3) the **other class** represents any in-water objects that can be risky to maritime navigation, for example, floating docks, fishing nets. We provide ontology documentation for labeling annotation consistency and dataset usage .

For the images, we used the 3rd party Amazon AWS Mechanical Turk annotation service in addition to the annotation by team members using the open-source Anylabeling [33] tool and model-assisted labeling using Meta Research’s Segment Anything Model (SAM) [34]. For the LiDAR point clouds, we adapted an open-source labeling tool [35] for our purpose. We first conducted manual annotations and then resized them to bounding boxes that tightly contains the point cloud within it, while maintaining the yaw of the manually

annotated bounding boxes. For both, we ran three rounds of annotation review by the expert team members for quality control.

We provide the label format in a standardized way along with converter implementations, such as YOLO format, KITTI format, unified normative, so that users can apply the dataset to different applications. The point cloud label contains $\{x, y, z, dx, dy, dz, \text{yaw}, \text{class}\}$ information. We only provide the yaw angle, assuming the roll and pitch remain approximately zero. Even if in rough water conditions this assumption might not hold, roll and pitch information is typically not necessary for ASV 2D navigation. For consistency of labeling in one frame of an image and a point cloud with its quality, we used a custom tool to extract the same object across the modalities (Fig. 3b). For the KITTI label format, we consider the annotation of an object as valid, only if they are located within FoV of both camera and LiDAR, following KITTI benchmark guideline [1].

D. Dataset Structure

The overall structure of our dataset is shown in Fig. 5. The dataset is divided into three subsets: *train*, *validation*, and *test*. We define a sequence as a 60-second event involving object encounters at a specific geographical location, including the Barbados, Busan, Lake Sunapee, and Lake Mascoma. The folder structure is organized into subdirectories based on annotations, information, and sensor modalities per sequence. These sequences are further categorized into *closed-set* (sequences used for training) and *open-set* (sequences excluded from training). The *closed-set* sequences are split into *train*, *validation*, and *test* subsets, while the *open-set* sequences are reserved entirely for testing purposes. This partitioning enables a robust evaluation of both the performance and generalization capabilities of learning-based algorithms [36].

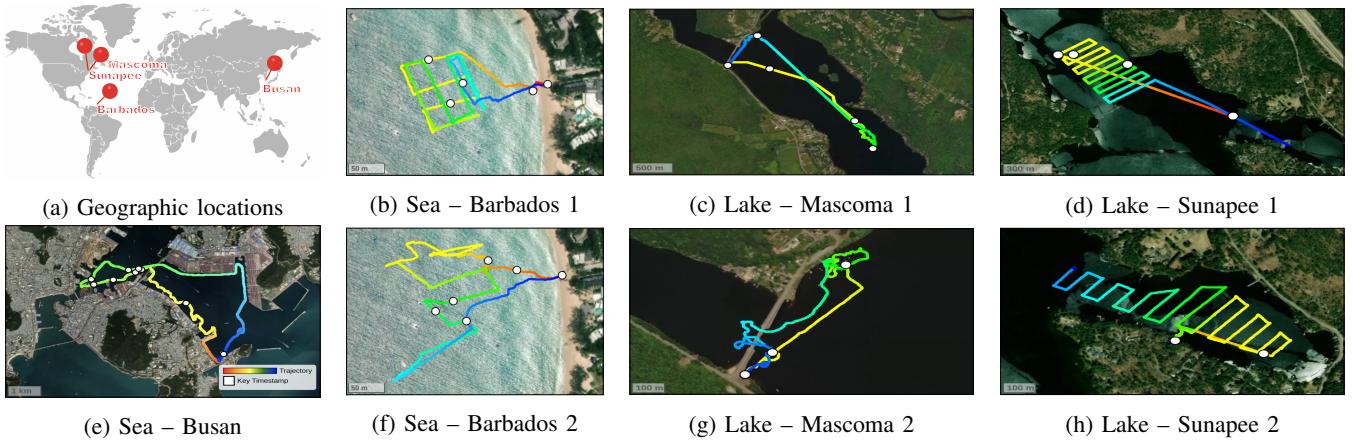


Fig. 4: Data collection trajectories in different locations, navigating from red to blue. white points are key frames with objects encountered and corresponding annotations in the dataset, defined as ‘sequences’.

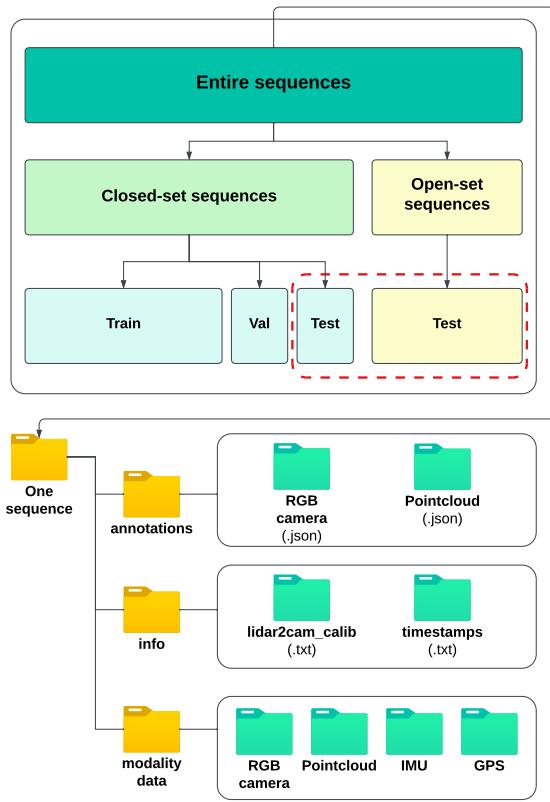


Fig. 5: Overall dataset structure.

IV. DATASET CHARACTERISTIC

A. Dataset Composition

As shown in Fig. 6, our maritime perception dataset consists of various objects in water under varying conditions collected by the sensor platforms onboard ASVs or onboard a human-driven ship. This annotated, ego-perspective dataset is the first in the maritime domain, to the best of our knowledge with sufficiently large number of annotated frames (total 11,561). We believe it will be useful for training, validating,

and benchmarking maritime perception.

The annotated class breakdown in the RGB camera data and LiDAR data can be found in Fig. 7, where the predominant class in both modalities is “ship,” followed by “buoy,” and then “other.” In the RGB camera data, there are 22874 ship annotations, 11337 buoy annotations, and 1833 other annotations. Similarly, in the LiDAR data, there are 22251 ship annotations, 15692 buoy annotations, and 1636 other annotations. The annotation resolution, made via 2D and 3D bounding boxes, respectively, can be characterized by its pixel area (Fig. 8(top)) and the number of LiDAR points (Fig. 8(bottom)). This resolution is inherently limited by the underlying sensor resolution as well as other confounders related to the modality (e.g., illumination for RGB Cameras) and others related to the maritime domain (e.g., in-water dynamics). Still, this approach gives insight into the amount of available sensor information upon which to detect and classify objects.

For the majority of objects, the annotation resolution is in the lowest bin, where the ship class has the highest average pixel area (mean: 4197.1, standard deviation: 10194.2, median: 794.0), followed by other (mean: 157.4, standard deviation: 551.7, median: 28.0), and, finally, buoy (mean: 218.3, standard deviation: 301.2, median: 38.0). Generally, the point cloud data follows the same trend where ships have the highest average point-cloud points (mean: 360.1, standard deviation: 1477.2, median: 37.0), followed by other (mean: 15.8, standard deviation: 17.8, median: 8.0), and, then, buoy (mean: 11.0, standard deviation: 35.6, median: 2.0). Of note, are the high standard deviations, a phenomena also captured by the long-tailed nature of the distributions in Fig. 8, meaning that there is a large amount of heterogeneity within the same class.

In terms of environmental conditions, the data is composed of 79.9% for day time, 14.9% for “dusk”, and 5.2% for night.

B. Dataset Complexity

As described in detail below, we propose novel metrics (e.g., BEVE-P, BEVE-V, DVE) in addition to existing metrics

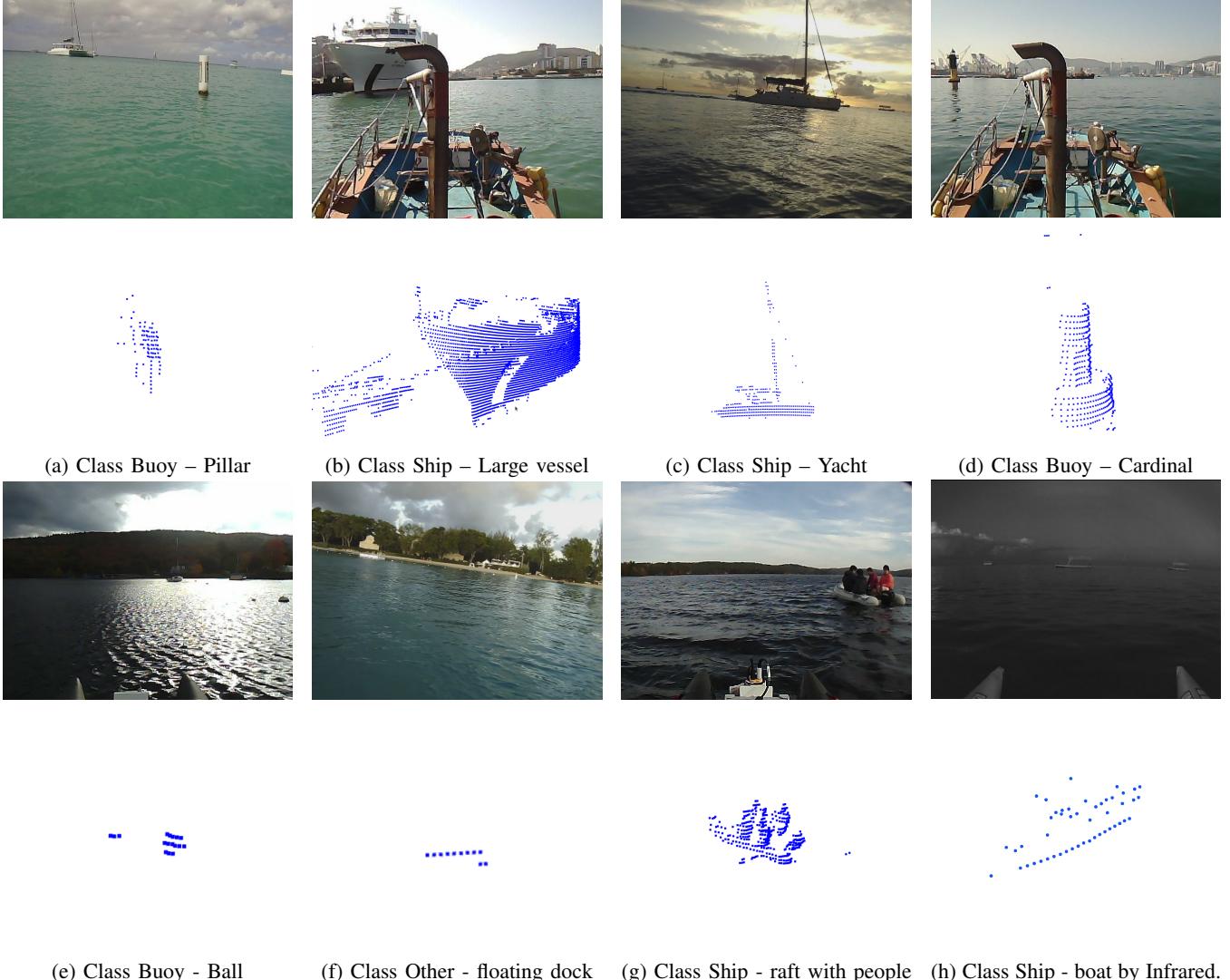


Fig. 6: In-water objects under varying environmental conditions in our dataset. (*top*): images; (*bottom*): point clouds. Note that the view angle of the point clouds is adjusted for the best visualization, regardless of the corresponding image of the object.

(e.g., image entropy, occlusion percentage) in the literature that quantitatively evaluate the dataset’s characteristics with respect to the maritime domain to help analyze future benchmark algorithms.

1) Image Complexity: Image entropy indicates the variation or complexity of an image at the grayscale distribution. In general, a low value corresponds to less edges and corners and possibly fewer interesting features, while a high value corresponds to an image with significant amount of texture.

We evaluate image complexity with three entropy metrics: delentropy, object-level entropy, and texture-level entropy. For **delentropy** metric, we first applied the Sobel operator to approximate the gradients along the vertical and horizontal directions and afterwards calculated the Shannon entropy. We take inspiration from the evaluation criterion in the work by [37], an underwater dataset – where image-based object detection algorithms typically implement some preliminary

edge detection processing. Note, instead of the Sobel filter, another edge detection algorithm, such as Canny Edge detector, can work as well. The traditional **object entropy** and **texture entropy** metrics are similar in that they are directly calculating the Shannon entropy, but with different sized template discs – object-level with a disc of 10 pixel radius and feature-level with a disc of 5 pixel radius. Here, there is no prior applied edge-detection based filter.

Fig. 9 depicts the results of image complexity, according to the above three entropy metrics, for our dataset as well as for four other comparison datasets: Pohang [18], MaSTR1325 [8], MODD2 [10], and USVIInland [16]. Compared to the Pohang dataset, our dataset includes more diverse imagery scenes. On the other hand, the image complexity of the USVIInland dataset is comparable to our dataset – not surprising, given the various textures of nearby trees, rocks, tunnels, and houses in inland waters. While

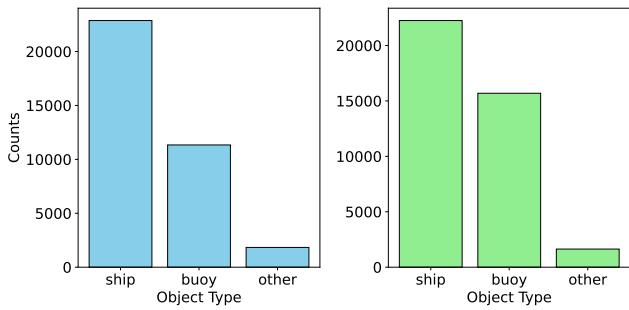


Fig. 7: Labeled objects by class present in the dataset in the RGB image modality (*left*) and the LiDAR modality (*right*).

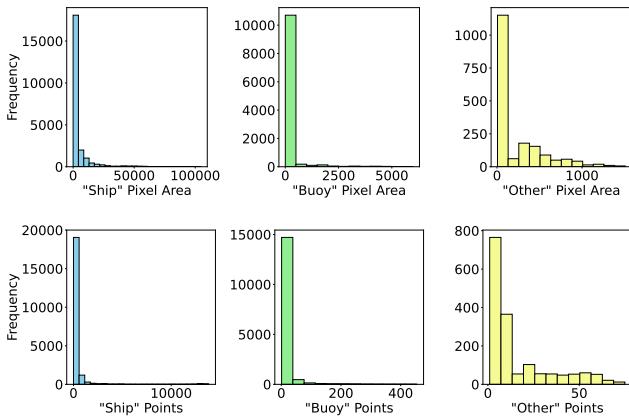


Fig. 8: The distribution of labeled object pixel area in the RGB Camera modality (top) and of LiDAR points (bottom) by class. Both pixel area and number of LiDAR points exhibit similar distributions.

the MaSTR1325 and MODD2 datasets (both from the same authors) have a greater range of complexity compared to our dataset – much of their images have small objects (relative to image size) and due to observable off white-balancing, the pixel intensity values are within a smaller range – leading to many images corresponding to low entropy values. Our dataset shows a wide diversity of images, and with better on-camera white-balancing, our images have greater pixel intensity variations.

2) **LiDAR Complexity: Birds-Eye-View Entropy** with Pillar/Voxel (BEVE-P, BEVE-V): Measures the *point cloud complexity* with respect to point pillar/voxel bin based on $BEV = \sum_{i=1}^K [\frac{k_i}{K} * \log(\frac{k_i}{K})]$ where i stands for each pillar or voxel, K total number of points in that specific frame, and k_i the number of points per each pillar or voxel.

Distance Variability Entropy (DVE) Measures the *point cloud complexity* with respect to point pillar/voxel bin based on $DD = \sum_{i=1}^N [\frac{n_i}{N} * \log(\frac{n_i}{N})]$ where i represents the i -th predefined distance interval, N total number of points in that specific frame, and n_i is the number of points in the respective distance bucket ring.

Fig. 10 shows the proposed complexity metrics of the dataset within the collected point clouds, indicating that we

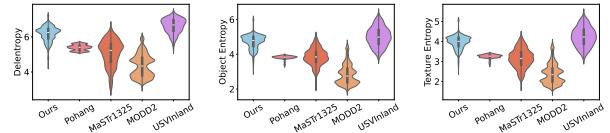


Fig. 9: RGB image complexity comparisons between our dataset (*light blue*) and four other maritime perception image datasets Pohang [18], MaSTR1325 [8], MODD2 [10], and USVInland [16].

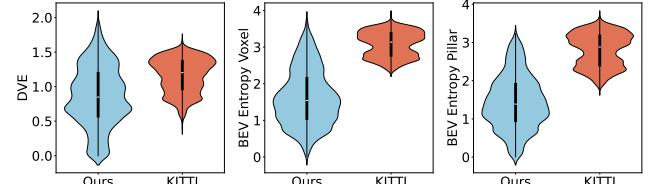


Fig. 10: Point cloud complexity comparison between our dataset (*light blue*) and KITTI [1] (*red-orange*). Across DVE, BEV Entropy Voxel, and BEV Entropy Pillar, our dataset shows a greater range of point cloud complexities.

have varying spatial distributions of in-water objects.

V. PERCEPTION BENCHMARKS

We ran the perception benchmark on our proposed datasets on detection tasks, i.e., **object detection** and **object classification** and developed the necessary conversion tools. We used a computer equipped with an Intel i7-7820X 8-core 3.6 GHz processor, 32 GB RAM, and NVIDIA GPU RTX 3090 Ti with 24 GB VRAM. We evaluated benchmark algorithms, offering insights into the applicability and adaptability of these benchmarks in the maritime domain.

A. Image-based benchmarks

While many real-time RGB image object detection approaches exist, we selected 2 representative models to provide a benchmarking of this dataset upon: YOLOv9 [38] and RT-DETR [39]. We specifically benchmark using real-time detectors as the ego-centric ASV perspective of this dataset lends itself to use in real-time, on-board object detection use cases. Based on that criteria, we selected a model from the popular You Only Look Once (YOLO) object detector lineage, which uses a Convolutional Neural Network (CNN) backbone approach and a newer Transformer-backbone approach based on the Detection Transformer [40] (DETR), that was adapted for real-time (RT) use.

Both models were trained for 300 epochs and we used the default hyperparameters from the YOLOv9 [41] and RT-DETR [42] open-source implementations. From their reference implementation, a confidence threshold of 0.25 and an Intersection over Union (IoU) threshold of 0.45 for non-maximum suppression was applied to post-process outputs before compiling results. For consistent comparison across 2D object detection methods, we use the mean Average Precision (mAP) metric. Validation and test set results can

be found in Table II and example detections in Fig. 11. The qualitative examples are from 3 of the dataset’s locations: Barbados, Lake Mascoma, and Busan Port, to show several multi-object encounters with ship, buoy and other labeled objects.

From the results of both models, qualitative and quantitative, out-of-the box models have room for improvement – especially on the buoy and other classes. It is clear that (a) there are relevant image-only features to train object detection models and (b) that this dataset represents a challenging detection task, characteristic of the maritime ASV environment.

The heterogeneity of maritime objects, variable environmental conditions, and in-water dynamics make this a difficult RGB-camera-only robotic vision problem – one that the addition of LiDAR data can help address.

B. LiDAR-based deep learning benchmarks

We analyzed the performance of LiDAR based methods on 3D and Bird’s Eye View (BEV) detection in the maritime domain. We selected 5 state-of-the-art LiDAR-only 3D object detection models – based on the following categorizations:

- **Voxel-based:** PointPillars [25], SECOND [43], Voxel-RCNN [46];
- **Point-based:** PointRCNN [44];
- **Point-voxel-based:** PV-RCNN [45].

We adapted OpenPCDet [50] and additional source code [43], [48] for benchmark comparisons tailored to our maritime dataset.

We followed each paper’s guideline on setting the hyper-parameters and used the suggested values when possible. We increased the point cloud range and the voxel size to account for the longer distances between the ASV and obstacles. Each method was trained for 200 epochs with early stopping once the model stops improving.

For consistent comparisons across LiDAR-only and fusion methods, we evaluated and reported performance for objects within both the camera and LiDAR FoV, consistent with KITTI benchmarks [1]. Note that our ground truth labeling provides a 360° FoV from the LiDAR used on our platforms. Performance was compared based on Average Precision (AP) at IoU thresholds of 0.7 and 0.5, evaluated for both BEV and 3D detection. We focused on the **ship** class for performance comparison due to the sparsity and challenges posed by features associated with small objects in the **buoy** and **other** classes, which are typically represented by only 1–2 LiDAR points, as shown in Fig. 8(bottom).

The evaluation results (Table III) for BEV detection are comparable to those of previous work [22], which used simulation results tested on 2D. Instead, our benchmark comparison extends applicability to the 3D domain with real-world data. Among LiDAR-only methods, SECOND consistently performed well in BEV AP. This can be attributed to its voxel-based representation and efficient sparse convolution, which effectively capture large-scale geometric features. These characteristics make SECOND particularly robust for BEV representations, where preserving spatial structure is

critical. In contrast, Voxel-RCNN excelled in 3D AP metrics. Its success stems from leveraging high-resolution voxel grids combined with an accurate region proposal network, enabling more precise object localization in 3D space. On the other hand, PointRCNN, which relies solely on raw point clouds and bypasses voxelization, is limited in its ability to efficiently extract global features, making it less effective in sparse maritime environments. Meanwhile, PV-RCNN, employing a hybrid approach that combines voxel-based feature extraction (for global context) with raw point-cloud features (for local precision), was better than PointRCNN by balancing global and local feature extraction.

C. Fusion-based deep learning benchmarks

We evaluated the following 3 state-of-the-art 3D object detection fusion methods:

- **Sequential fusion:** PointPainting [47] based on DeepLabV3 [51] and PointPillars;
- **Decision-level fusion:** CLOCs [48] based on the detection of YOLOv9 [38] and SECOND; and
- **Feature-level fusion:** Focal Conv-F [49].

As shown in Table III, fusion-based methods demonstrated superior performance across most metrics, particularly at stricter IoU thresholds (0.7). Among these, Focal Conv-F achieved the best results in both BEV AP and 3D AP on validation and test datasets. Its effectiveness can be attributed to the seamless integration of complementary sensor modalities, enabling robust spatial feature extraction and superior object localization. While CLOCs and PointPainting performed competitively, their performance lagged at stricter IoU thresholds for 3D AP. CLOCs, which integrates predictions from multiple backbones, showed reduced performance in scenarios requiring high precision, likely due to a weaker emphasis on fine-grained feature alignment. Similarly, PointPainting’s reliance on segmentation quality and alignment resulted in lower performance in 3D AP metrics compared to Focal Conv-F.

We also provide a qualitative analysis across the 3D Object Detection benchmarks. Fig. 12 illustrates the results of a sequence (Mascoma Lake) on our *open-set* test data, which were excluded from all training steps. Consistent with the quantitative evaluation, SECOND and Focal Conv-F exhibited strong performance for ship detection.

VI. DISCUSSION

Based on our contribution of the first multi-modal dataset in the maritime domain and its utility for deep learning-based approaches, we identify and provide insights into the challenges and open problems for future tasks aimed at enhancing robust perception systems in maritime environments. Furthermore, we hope this dataset will provide the research community with a starting point to develop robust, novel methods for ASV perception. Given this work, it is our continuing hypothesis that multi-modal methodologies are essential for the development of robust ASV situational awareness given in-water dynamics, environment

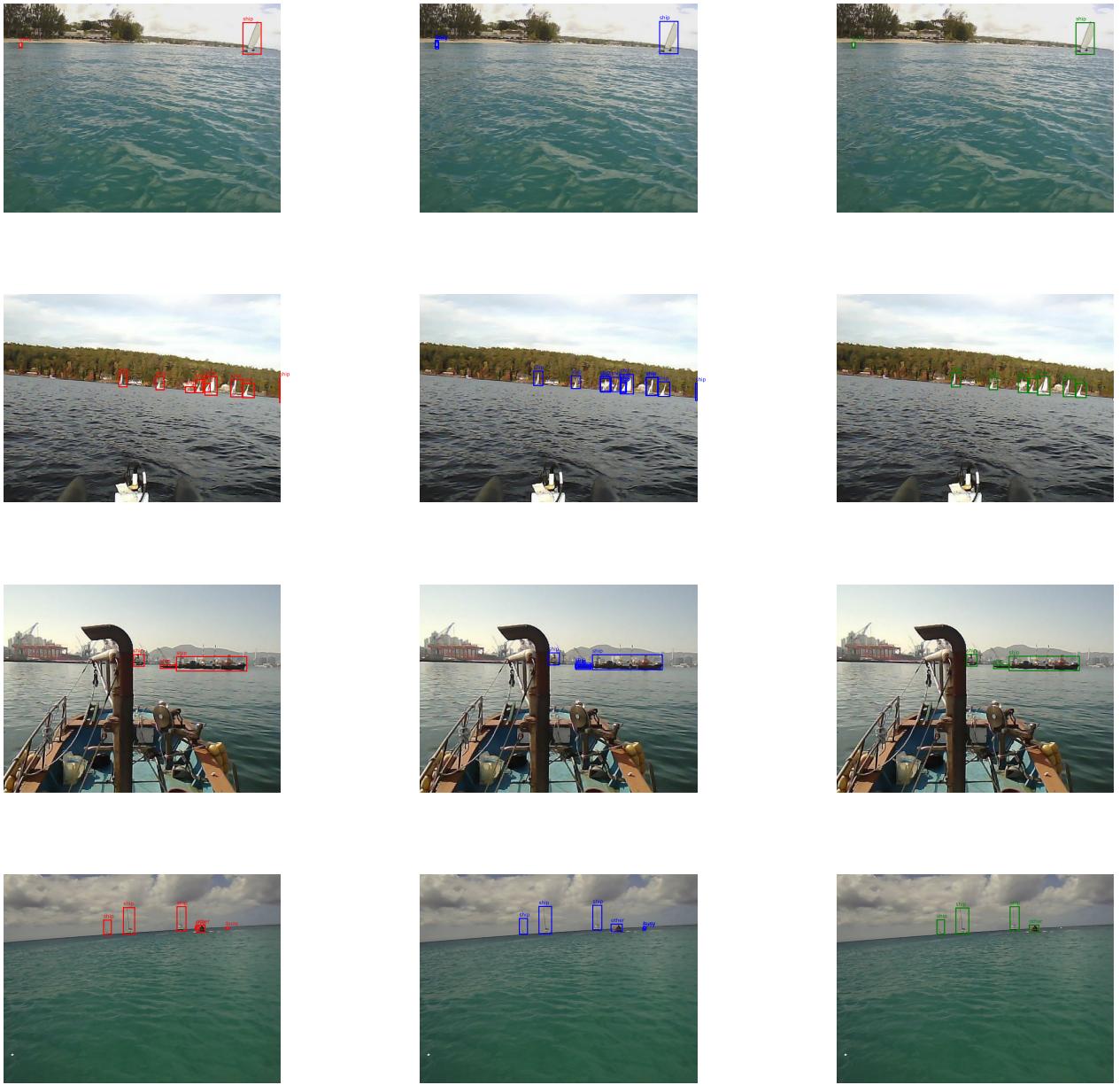


Fig. 11: Detection examples from the benchmark image models trained on the RGB image portion of the dataset, where the left column is groundtruth (red), the middle column is RT-DETR (blue), and the right column is YOLOv9 (green). While the models did learn to predict many of the classes, there is still much room for improvement that robotic perception methods adapted to the ASV domain could begin to address using this dataset.

TABLE II: Performance breakdown of 2 benchmark 2D image object detectors by class. mAP is reported via the aggregated IoU threshold from (0.5 to 0.95) per class.

Model	Aggregated mAP (0.5:0.95)		“ship” mAP (0.5:0.95)		“buoy” mAP (0.5:0.95)		“other” mAP (0.5:0.95)	
	Val	Test	Val	Test	Val	Test	Val	Test
YOLOv9 [38]	0.54	0.42	0.83	0.65	0.42	0.34	0.36	0.27
RT-DETR [39]	0.21	0.16	0.45	0.36	0.13	0.10	0.04	0.01

TABLE III: Comparison of validation and test results for LiDAR-based benchmarks (IoU thresholds of 0.7 and 0.5) for *ship* class objects. *Green* highlights the best performance across all methods, while *yellow* indicates the best performance among LiDAR-only methods.

Model	Modality	BEV AP (0.7)		BEV AP (0.5)		3D AP (0.7)		3D AP (0.5)	
		Val	Test	Val	Test	Val	Test	Val	Test
PointPillars [25]	LiDAR-only	28.01	17.32	57.22	50.77	4.23	3.14	30.30	30.07
SECOND [43]	LiDAR-only	34.29	27.68	56.95	52.36	8.93	10.17	40.70	40.67
PointRCNN [44]	LiDAR-only	3.24	3.11	23.93	21.48	0.32	0.43	2.91	2.66
PV-RCNN [45]	LiDAR-only	19.11	9.99	42.40	38.65	3.79	9.09	23.64	16.54
Voxel-RCNN [46]	LiDAR-only	33.36	27.50	54.55	50.69	12.90	13.46	41.96	43.03
PointPainting [47]	Fusion	30.51	25.42	57.92	46.10	10.05	12.95	42.54	37.67
CLOCs [48]	Fusion	32.02	21.76	56.68	49.47	9.69	8.28	45.38	41.10
Focal Conv-F [49]	Fusion	37.48	36.36	61.69	54.55	19.83	15.58	47.79	45.45

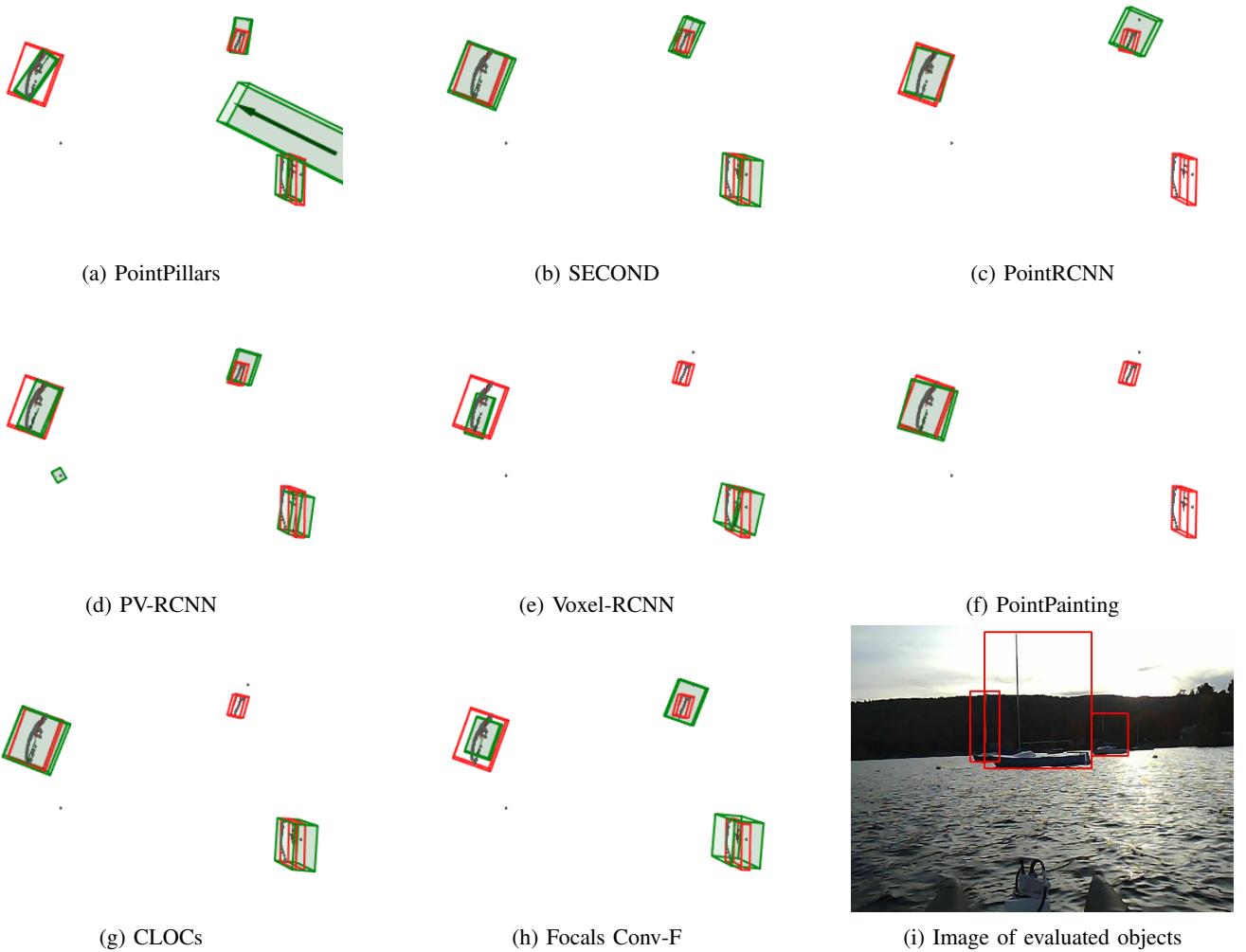


Fig. 12: Qualitative comparison of LiDAR-based and fusion object detection benchmarks tested on our dataset, shown from a bird's-eye view. The evaluated objects belong to the **ship** class within the FoV of both the camera and LiDAR, with ground truth bounding boxes depicted in red and predicted bounding boxes in green.

heterogeneity, and failures being inadmissible. To enable the development of these methods, open challenges include:

Maritime environments often feature **sparse** point clouds due to objects located at long distances and unstable measurements affected by the motions of both ego and target vehicles, as noted by [52]. Current detection methods strug-

gle to learn features from such minimal data, particularly for buoys and small objects. This highlights the need for models capable of accurately detecting and classifying objects even under sparse conditions. For example, as shown in Fig. 13, even a single LiDAR-detected point representing an object such as a buoy could lead to a collision if ignored. This

differs from other domains where they often use thresholds for a minimum number of points.

Generalizability remains another significant open challenge. For instance, LiDAR-based deep learning models (and many real-time image-based deep learning models) use anchors, which represent the predefined dimensions of bounding boxes, to enhance the accuracy and efficiency of object predictions. However, as shown by the range of the length (0.1 m - 123.5 m), width (0.1 m - 81.1 m), and height (0.1 m - 35.7 m) of the LiDAR annotations, object sizes in the maritime domain vary greatly – from small fishing boats to large commercial ships – all defined as “ships” under international maritime traffic rules [20]. Therefore, if hyperparameters, such as anchor dimensions, are not carefully chosen they may degrade the performance of detection benchmarks. Furthermore, all the point cloud detection benchmarks we utilized in our study relied on preset point cloud ranges. However, we observed cases where detected point clouds lay beyond the sensor’s nominal range (e.g., exceeding 120 m), particularly in open sea conditions. Aligned with maritime navigation principles – to focus on early detection and take large actions in ample time – predefined ranges and sizes must be thoughtfully selected. These parameters strictly constrain current learning-based methods, underscoring the need for models, such as anchor-free approaches, that can adapt to varying detection ranges and object dimensions.

Robustness against **misalignment** presents additional open challenges in the maritime domain. As observed in ground-based applications [53], [54], spatial/temporal misalignment that can come from factors such as noisy extrinsic parameters and the relative motion of ego and target vehicles on the water surface, is also prevalent in maritime environments, as illustrated in Fig. 14. Mechanical-level misalignments are particularly difficult to correct onboard due to the lack of fixed features on the water and the continuous motion influenced by hydrodynamics. These challenges highlight the need for in-water online calibration methods to enhance robustness. Additionally, annotations in the maritime domain naturally suffer from misalignment. Our dataset primarily considers z -axis orientation (i.e., yaw) in the labeling process. However, pitch and roll can significantly affect object detection and state estimation, particularly in the maritime context, where dynamic, non-stable characteristics differ from those in other domains (e.g., planar road surfaces). Generating accurate ground truth for pitch and roll orientations remains challenging but critical for improving detection and tracking performance in such environments. Addressing this open problem will likely be an important precondition to robust multimodal fusion methods in the maritime surface domain.

VII. CONCLUSION

This paper introduces the first publicly accessible multi-modal perception dataset for autonomous maritime navigation, focusing on in-water obstacles within aquatic environments to enhance situational awareness for ASVs. Our

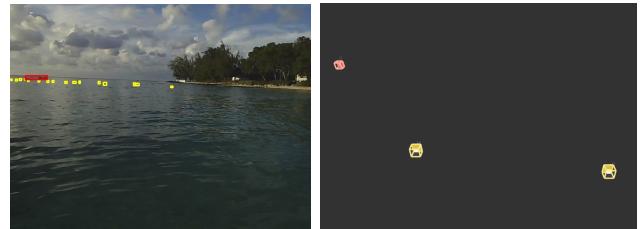


Fig. 13: Challenging sparsity example from Barbados sequence in our dataset – (yellow) buoys, (orange) floating dock. Although there are many objects in the image (*left*), the LiDAR measurement has only 3 objects while each of them has 1 point inside the bounding box (*right*).



Fig. 14: Alignment (*left*) and misalignment (*right*) of fused sensors (LiDAR and RGB camera) due to the ego- and obstacle-motion on the water, despite the same calibration parameters.

dataset, which includes a diverse range of in-water objects encountered under varying environmental conditions, aims to bridge the research gap in marine robotics by providing a multi-modal, annotated, and ego-centric perception dataset for object detection and classification. We also demonstrate the applicability of the proposed dataset using open-source deep learning-based perception algorithms that have proven successful in other domains. Additionally, the development and analysis of this dataset offer foundational insights for advancing perception tasks in the maritime domain.

Future work will focus on designing adaptable and robust deep learning models capable of addressing domain-specific complexities while aligning with practical maritime needs. This includes integrating additional sensor configurations under diverse weather conditions (e.g., rain, snow), such as marine RADAR and wide-field-of-view cameras. Furthermore, we plan to extend this work to the object tracking task and continue to explore multi-modal modeling for ASV perception using this dataset. These advancements will be crucial for enhancing situational awareness, safety, and efficiency in real-world autonomous maritime systems, addressing high-impact societal needs such as search and rescue, environmental monitoring, and transportation.

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