Department of Mechanical Engineering

Faculty of Engineering Science

MarRI-UK: Postgraduate Conference

Enhancing Maritime Environment Perception with 3D LiDAR: A Novel Framework for Robust Detection and Tracking of Floating Objects by Unmanned Surface Vehicles

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Unmanned Surface Vehicles

Fig. 1. Maritime Robotics ‘The Otter USV’. [1]

Fig. 2. Ocean Alpha ‘M75’. [2]


Fig. 3. Ocean Power Technologies ‘WAM-V 22’. [3]

- Low development and operational costs
- Improved personnel safety and security
- Extended operational range, higher precision, and reliability
- Greater autonomy
- Flexibility in sophisticated environments

[1] Maritime Robotics, “A closeup of the Otter USV,” https://www.maritimerobotics.com/otter (accessed Apr. 10, 2024).
[2] OceanAlpha, “Autonomous Surveillance & Rescue Vessel,” https://www.oceanalpha.com/product-item/m75/ (accessed Apr. 10, 2024).
[3] OPT, “WAM-V 22 Rugged and relentless,” Ocean Power Technologies, https://wam-v.com/bestsellers (accessed Apr. 10, 2024).

Environment Perception

- Environment perception is an essential aspect of automated vehicles.
- The relevant technologies have made significant progress in ground vehicle applications, but show a relatively slower pace in the USV domain.
    - ➢ Impact of wind, wave and current on ship motions.
    - ➢ Impact of sea fog and water reflection on sensor performance.
    - ➢ Target objects have a wide rang of sizes.

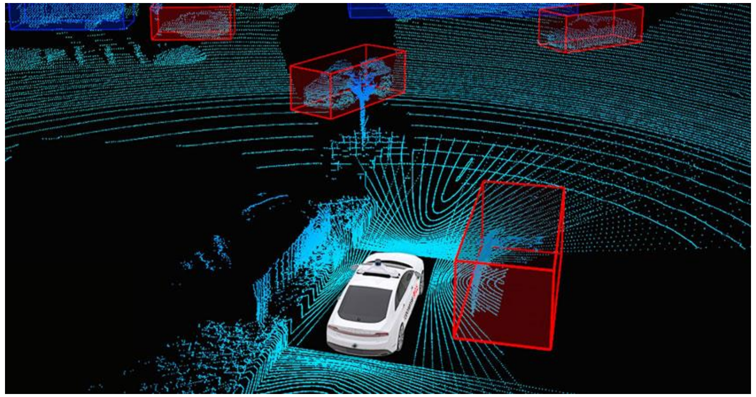


Fig. 4. LiDAR-based Perception for UGV. [4]

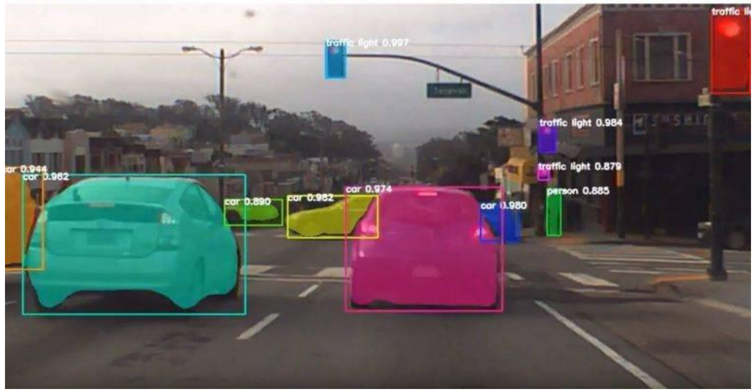


Fig. 5. Image-based Perception for UGV. [5]

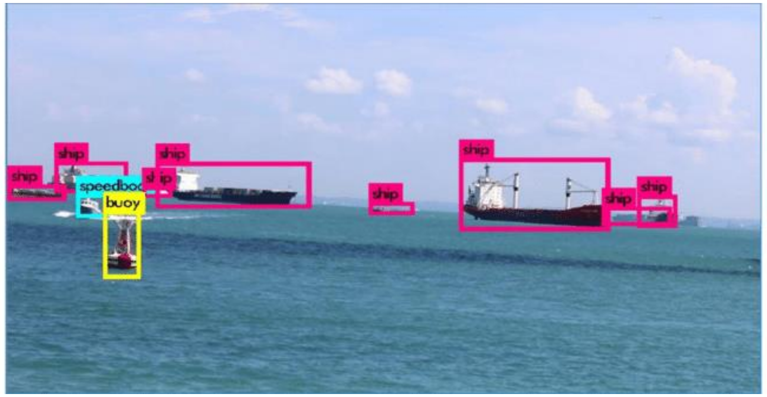


Fig. 6. Image-based Perception for USV. [6]

[4] IOT Automotive, "The Latest Robosense LiDAR Perception Solution Will Support ROBO Taxi Development," https://iot-automotive.news/the-latest-robosense-lidar-perception-solution-will-support-robo-taxi-development/ (accessed Apr. 10, 2024).
[5] CBINSIGHTS, "Unbundling The Autonomous Vehicle," https://www.cbinsights.com/research/startups-drive-auto-industry-disruption/ (accessed Apr. 10, 2024).
[6] S.-J. Lee, M.-I. Roh, and M.-J. Oh, "Image-based ship detection using deep learning," Ocean Systems Engineering, vol. 10, no. 4, pp. 415–434, Dec. 2020 [Online]. Available: https://www.mdpi.com/1424-8220/23/19/8093

Image-based Perception

Image-based perception can generally separated into detection and segmentation methods.

Limitations:

- Detection quality is heavily influenced by the environment.
- Cannot directly provide real-world position information for detected targets.

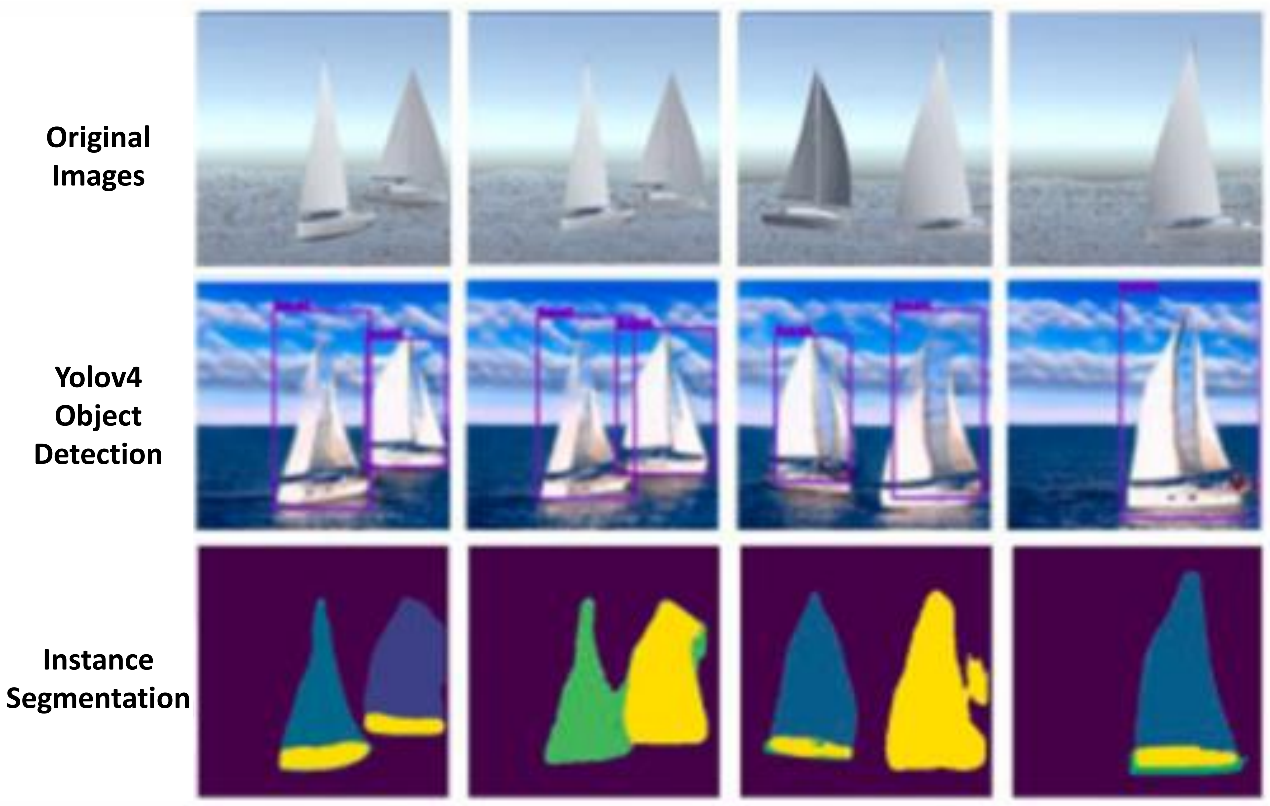


Fig. 7. Image-based perception in Maritime Application. [7]

[7] Y. Dong, P. Wu, S. Wang, and Y. Liu, "ShipGAN: Generative Adversarial Network based simulation-to-real image translation for ships," Applied Ocean Research, vol. 131, 2023, Art. no. 103456. [Online]. Available: https://doi.org/10.1016/j.apor.2022.103456

LiDAR-based Perception

Benefits:

- Robustness under various environment conditions.
- The point cloud data naturally include precise spatial locations.

Limitations:

- Complexity of processing point cloud data.
- Data resolution, particularly at longer distance, is suboptimal.

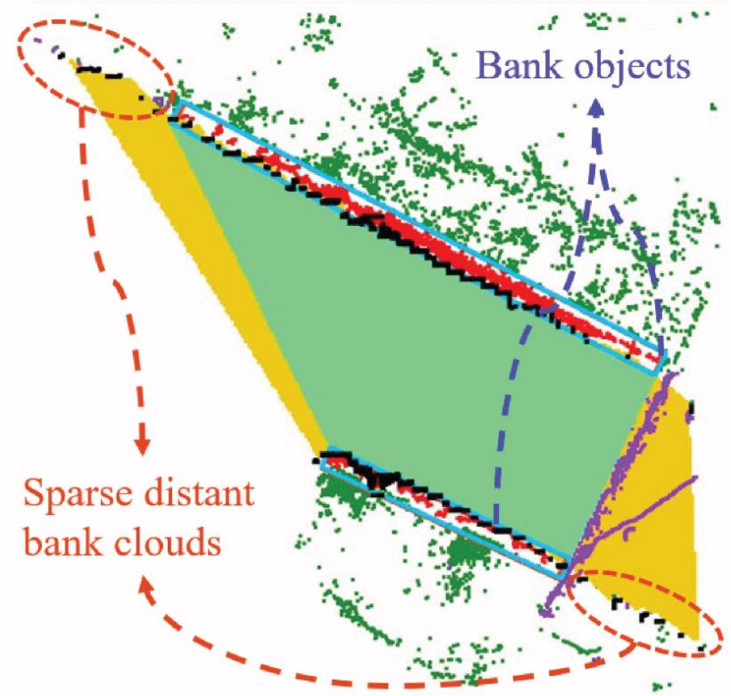


Fig. 8. LiDAR-based Navigable Region Detection. [8]

[8] Shan, Y., Yao, X., Lin, H., Zou, X., & Huang, K. (2021). Lidar-Based Stable Navigable Region Detection for Unmanned Surface Vehicles. IEEE Transactions on Instrumentation and Measurement, 70, 1–13. [Online]. Available: https://doi.org/10.1109/TIM.2021.3056643

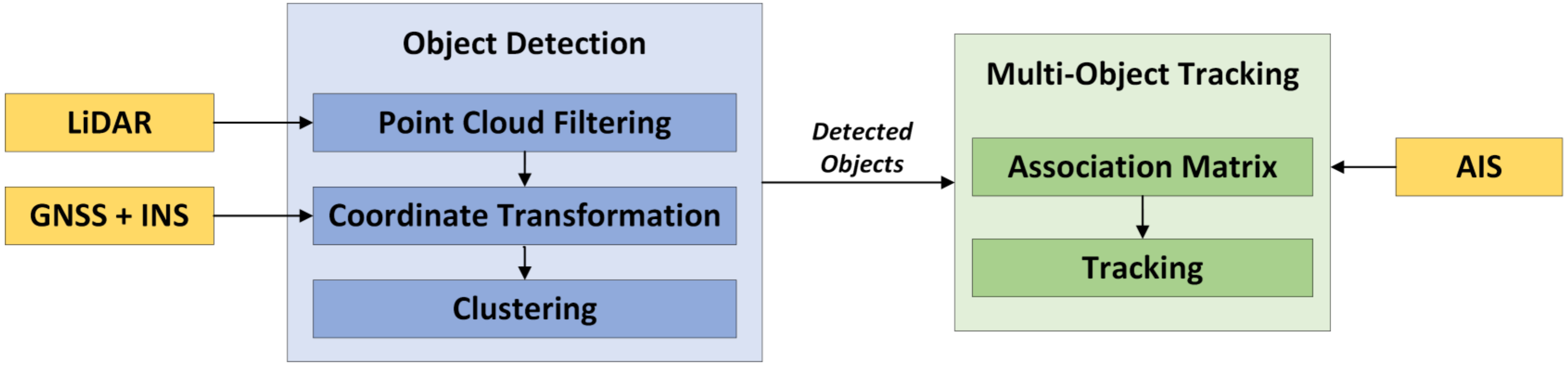
Related Works

Object Detection:

- Clustering-based object detection, e.g. Euclidean & DBSCAN
- Deep learning-based object detection

Multi-Object Tracking:

- Filter-based Multi-object tracking fusion with extra measurements, such as AIS data.



Aim and Objectives

Aim:

- To develop a robust LiDAR-based perception framework for port area surveillance.

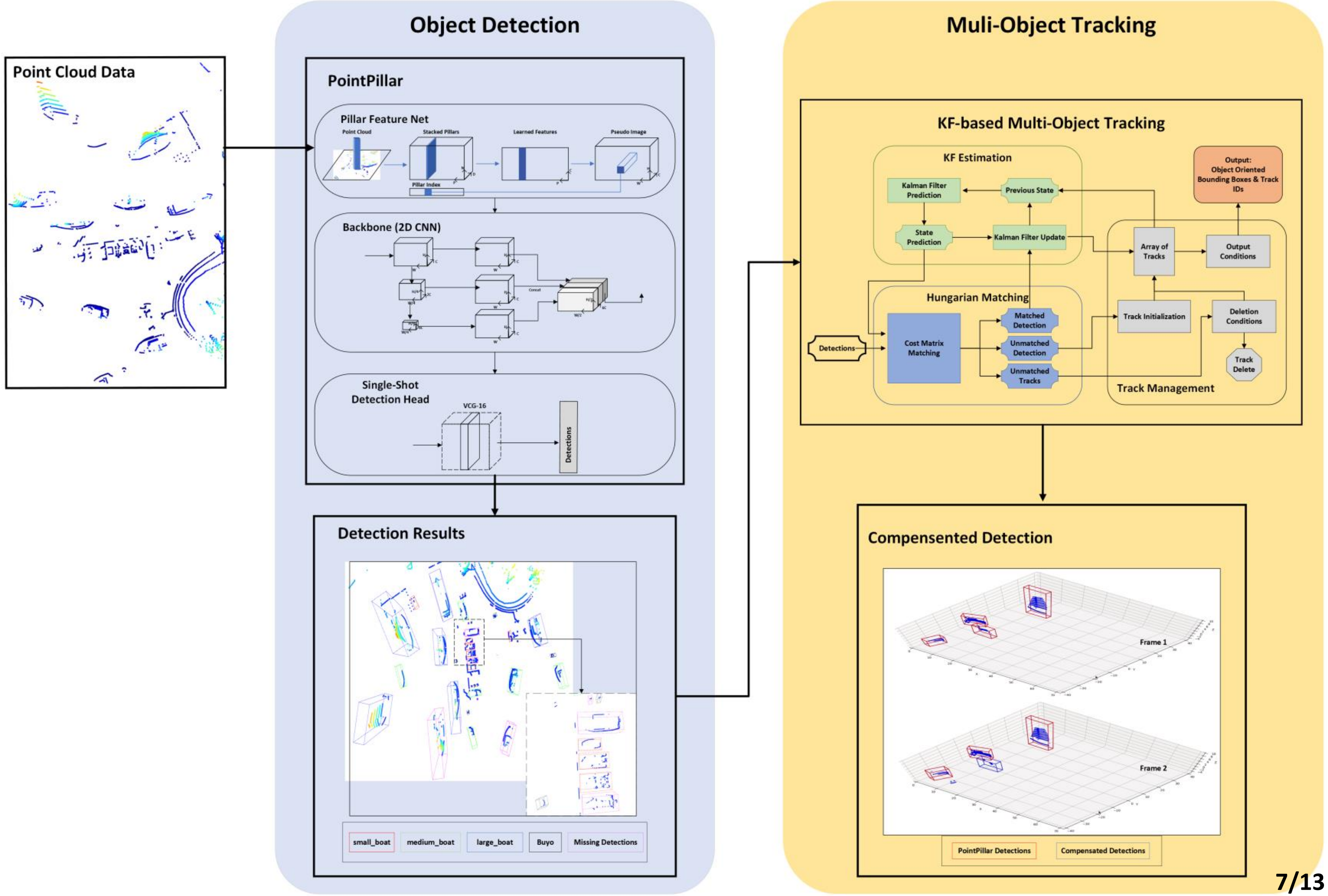
Objectives:

- Utilize a CNN-based method, specifically PointPillars, to process 3D point clouds and accurately detect floating objects on the water surface.
- Propose a tracking algorithm that combines the Kalman Filter and the Hungarian method for continuous detection on USVs, relying on detection results only.

Methodologies

- Object detection modules process the raw point cloud data and return the detected objects with their class and oriented bounding box.

- Multi-object tracking module receives the detection results to address the issue of discontinuous detection caused by the motion of USVs.

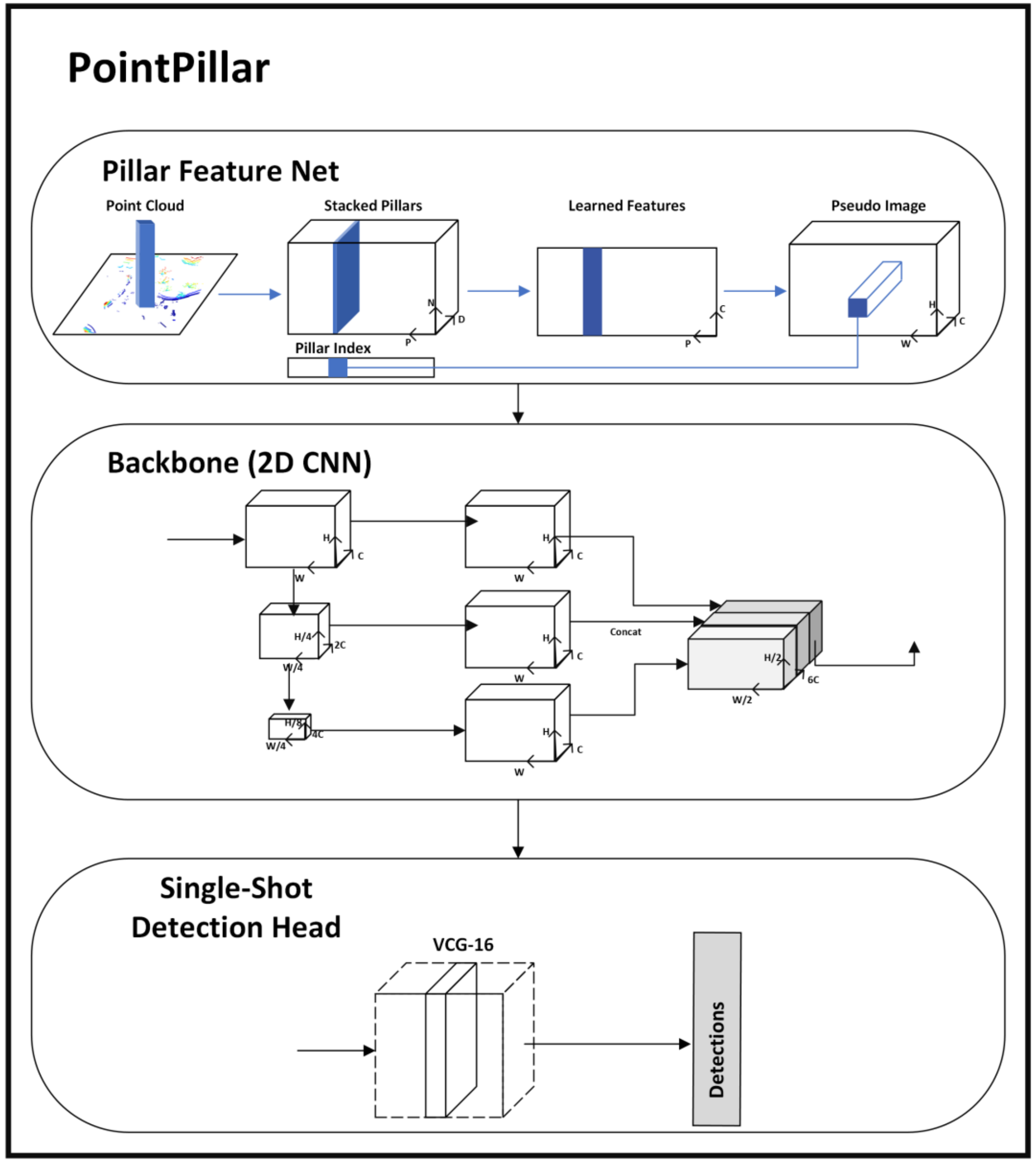


PointPillars

- PointPillar network beginning with a ***feature encoder network*** that transforms 3D point cloud data into a streamlined 2D pseudo-image.

- Pseudo-image then refined by a ***2D convolutional backbone***, yielding a high-level representation.

- The last step of this process is finished through a ***detection head***, which is responsible for classifying objects and regressing their 3D Obbxs.



KF-based Object Tracking Algorithm

Algorithm 1: KF-based Multi Object Tracking

Input: **Current frame detections,** Q_t

Output: **Tracked objects in the current frame,** $Q_{tracked}$

Matching: $Match \longleftarrow Hungarian\_Matching_{(Q_t, Q_{tracked,t-1})}$

For each $q \in Q_t$ **and** $p \in Q_{track,t-1}$ **do**

  if $Match(q) = NULL$

    $new\_object \longleftarrow Kalman\_Initialize(q)$

    $trackID \longleftarrow trackID + 1$

    Append new_object **into** $Q_{tracked}$

  elif $Match(q) = p$ **for some** $p \in Q_{tracked,t-1}$

    $matched\_object \longleftarrow Kalman\_Correct(p, q)$

    Append $matched\_object$ **into** $Q_{tracked}$

  else $Match(p) = NULL$

    if $missing\_match < 3$

      $missing\_object \longleftarrow Kalman\_Predict(p)$

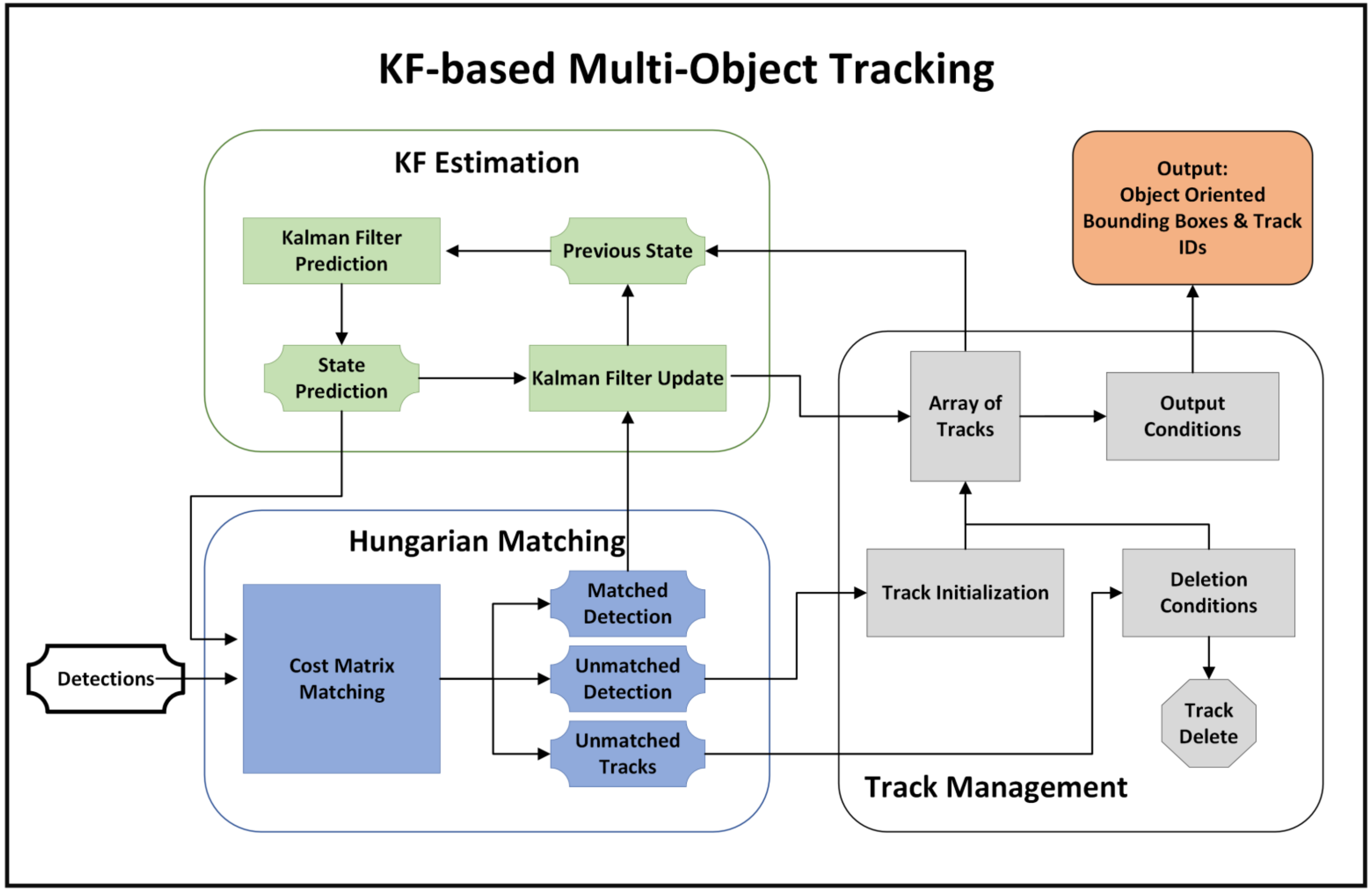
      $missing\_match \longleftarrow missing\_match + 1$

      Append $missing\_match$ **into** $Q_{tracked}$

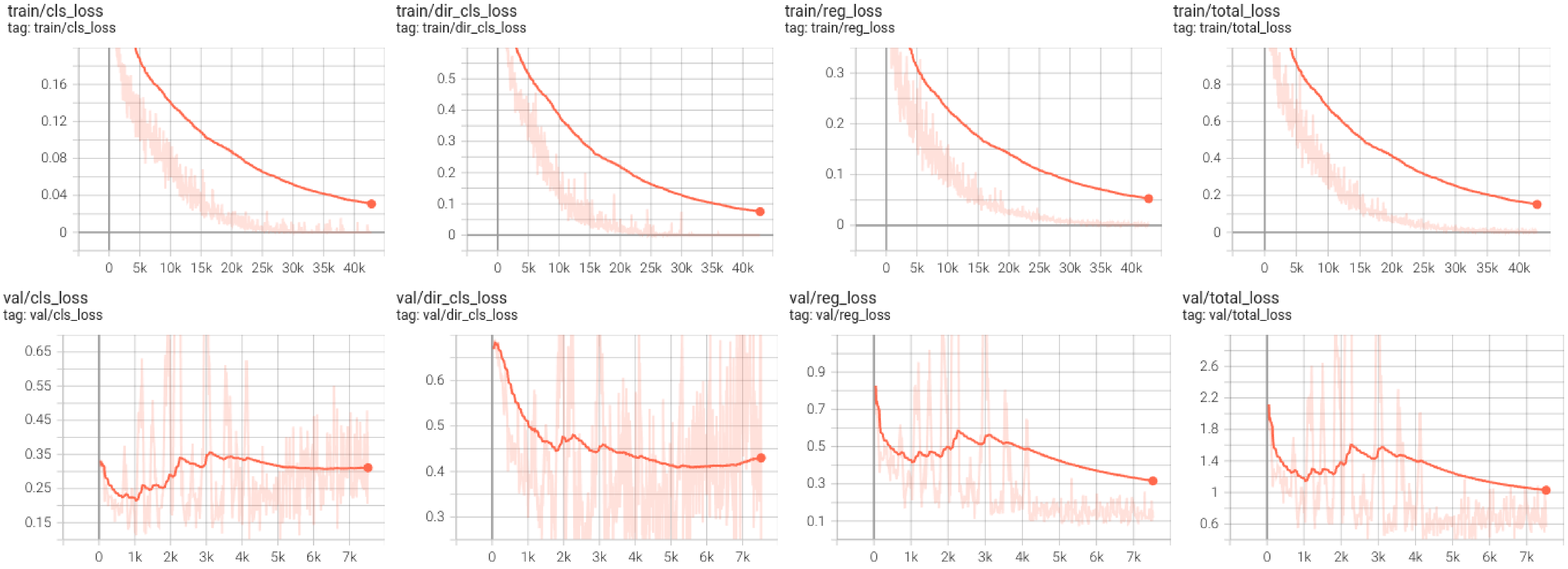
    end if

  end if

end for



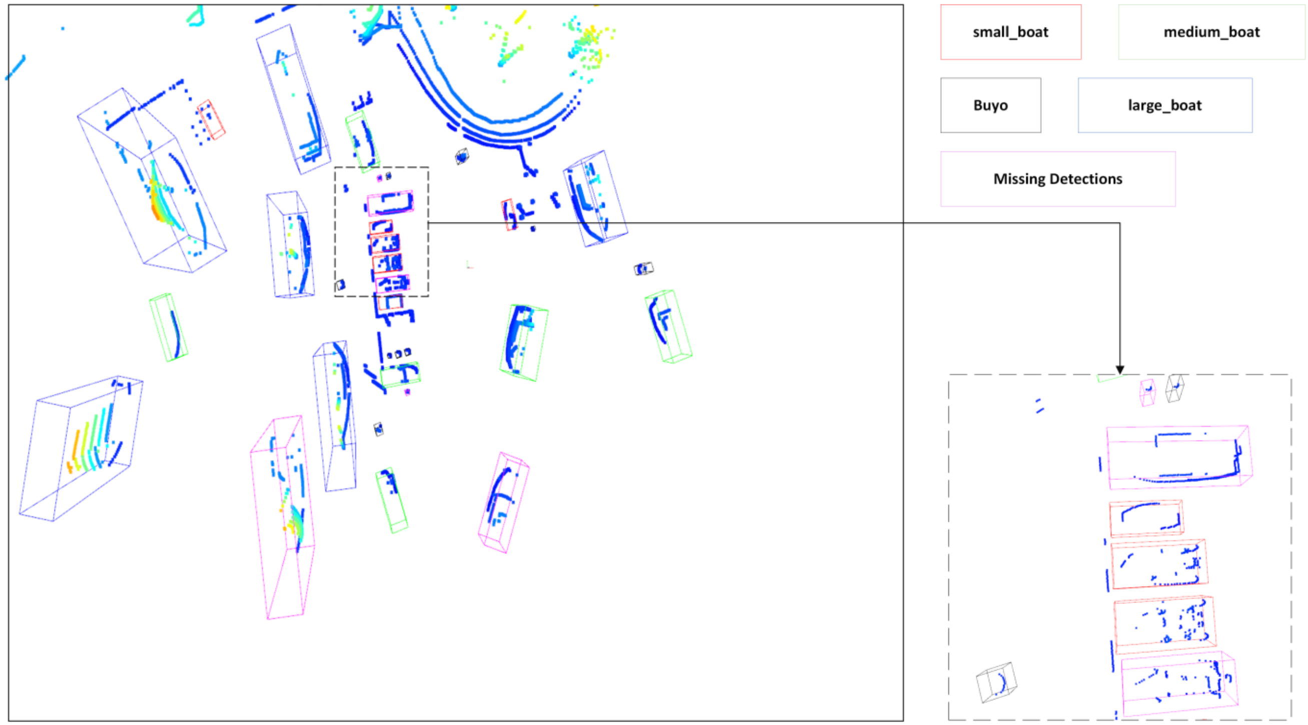
PointPillars Training & Evaluation



- *Computing system equipped with an AMD EPYC 7T83 CPU, an NVIDIA GeForce RTX 4090 GPU.*
- *The dataset utilized for training the PointPillar model was generated through simulation using ROS.*

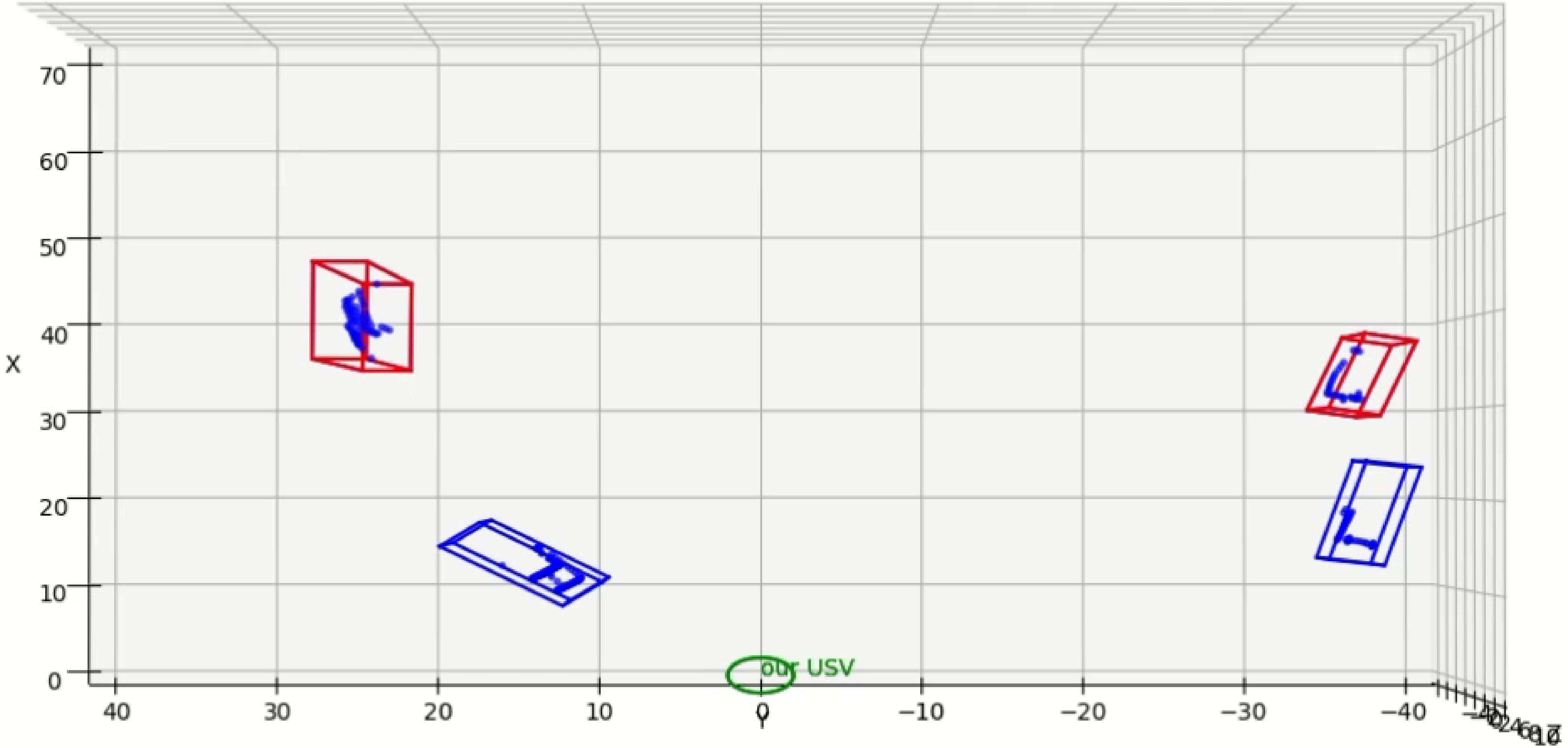
PointPillar Results

Method	LiDAR Layers	Average Percentage (%)				mAP (%)
		Small_boat	Medium_boat	Large_boat	Buyo	
PointPillar (ours)	16	59.3	63.4	71.4	43.2	62.5
PointPillar (Lin et al. [9])	16	-	-	-	47.1	60.8



[9] *Lin, J., Diekmann, P., Framing, C.-E., Zweigel, R., & Abel, D. (2022). Maritime Environment Perception Based on Deep Learning. IEEE Transactions on Intelligent Transportation Systems, 23(9), 15487–15497. [Online]. Available: https://doi.org/10.1109/TITS.2022.3140933*

Object Tracking Results



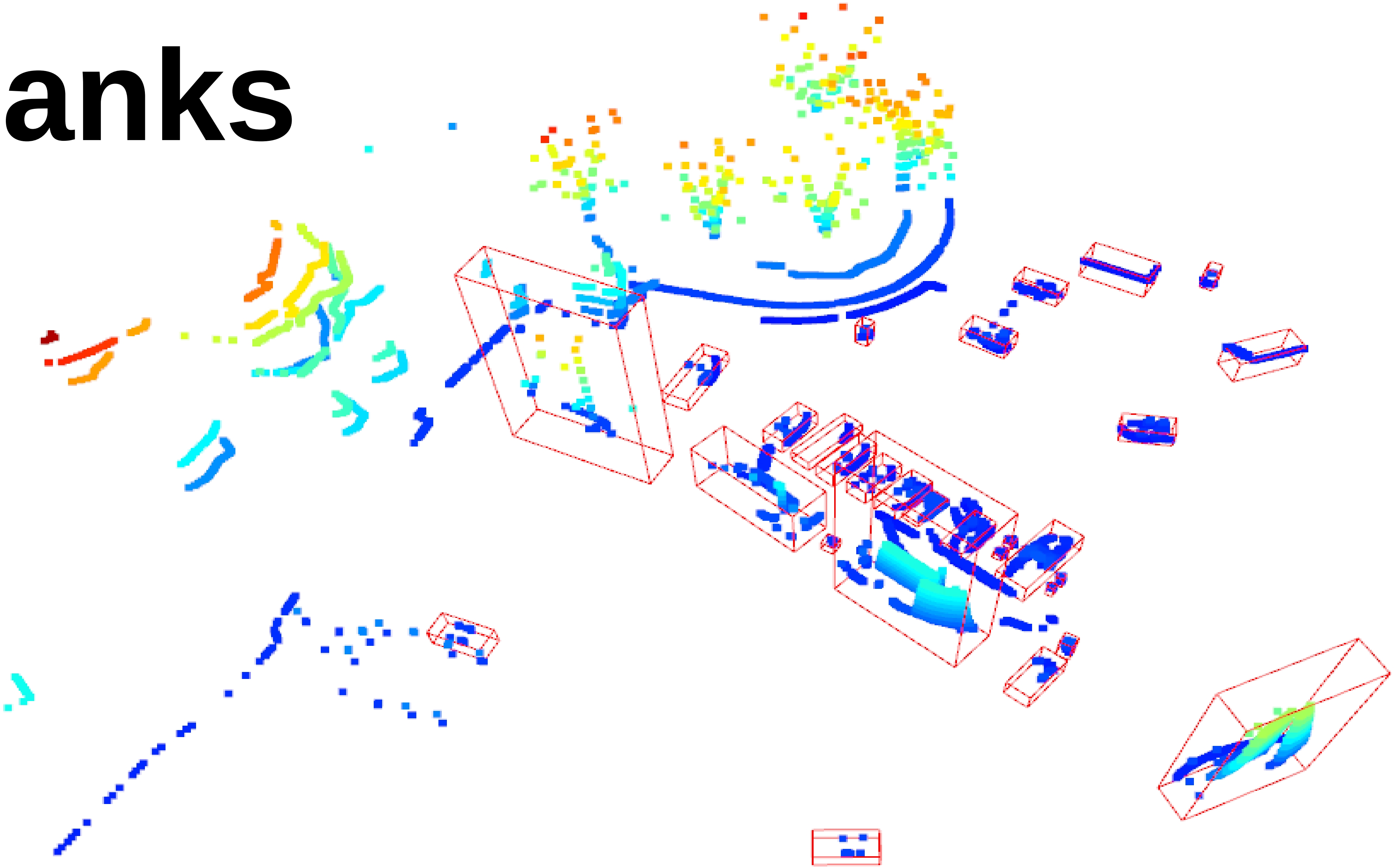
Conclusion and Future Works

- **Our framework includes:**
  - Employing the deep learning network PointPillars for direct processing of LiDAR point clouds and detection of target objects.
  - Deploying a Kalman Filter for tracking detected objects using only detection input, enabling continuous and robust detection.

Experiments conducted in a port area simulated using ROS demonstrate that our proposed method achieves commendable performance.

- **Future Works:**
  - Collect real-world data to train and test our framework.
  - Refine our PointPillars by enabling Bayesian network integration.
  - Integrate our framework into Otter USV for field testing.

Thanks



References

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