

Navigating Polar Routes: An Open-Source Simulation Framework for Autonomous Shipping

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Abstract—This paper presents a comprehensive benchmarking tool for autonomous shipping in polar environments, addressing the growing interest in polar routes due to climate change and reduced Arctic ice coverage. While these routes offer significant economic and environmental benefits by reducing distance, fuel consumption, and emissions, they also present severe navigational challenges such as dynamic weather, unpredictable ice formations, and GPS degradation. We propose a simulation framework built on Gazebo—a high-fidelity, open-source platform widely used in robotics and autonomous driving—to evaluate SLAM and routing algorithms under realistic polar conditions. By leveraging sensor fusion techniques, including LiDAR, radar, sonar, and cameras, our framework facilitates rapid development and benchmarking of both traditional and reinforcement learning-based navigation strategies.

Index Terms—Polar shipping routes, SLAM, benchmarking, simulation, Gazebo

I. INTRODUCTION

Polar shipping routes have gained increasing attention in global maritime logistics due to climate change and the gradual reduction of Arctic ice coverage. These routes offer significant reductions in fuel consumption, distance, and overall transit time compared to traditional shipping pathways. Taking for instance the Northern Sea Route (NSR) [1], which connects Europe and Asia via the Arctic, allows for a much shorter journey between Murmansk, Russia, and Yokohama, Japan—approximately 5,770 nautical miles (10,686 kilometers)—whereas the same journey through the Suez Canal covers about 12,840 nautical miles (23,778 kilometers). This reduction in distance results in lower fuel consumption and decreased carbon emissions, highlighting the potential environmental and economic benefits of polar shipping routes [2].

However, navigation through polar regions presents significant challenges, including harsh and dynamic weather conditions, unpredictable ice formations, and poor GPS coverage. GPS reliability is reduced because of the low positioning of the satellites on the horizon, limiting the number of signals, while ice and atmospheric conditions can block or distort them, leading to errors in positioning. These factors create operational uncertainties that must be addressed to ensure safe and efficient transit. The integration of autonomous ships has the potential to enhance the reliability, efficiency, and safety

of Arctic and Antarctic shipping. Autonomous solutions can minimize human error, reduce crew-related risks, and optimize route planning to navigate through ice-laden waters more effectively.

A critical technology that can enable safe autonomous navigation in GPS-degraded environments, such as the Arctic, is Simultaneous Localization and Mapping (SLAM) [3]. SLAM allows vessels to construct real-time maps of their surroundings while simultaneously determining their position within that environment. By utilizing sensor fusion techniques—integrating LiDAR [4], radar, sonar, and inertial measurement units (IMUs)—SLAM-based navigation systems improve spatial awareness and obstacle detection, thereby enhancing the autonomous operation of vessels along polar shipping routes. These technologies are especially relevant for routes like the NSR, where real-time adaptation to ice conditions is crucial [5]. Despite the potential of these advanced methodologies, progress in the development and deployment of autonomous shipping technologies has been slow [6]. This stagnation is partly due to the lack of accessible, user-friendly tools that can support rapid iteration cycles. To address this research gap, there is a pressing need for platforms that are not only easy to use but also benefit from a large, established community, thus accelerating innovation and application.

The contribution of this paper is to provide such a platform: we established a comprehensive benchmarking tool for autonomous shipping in polar environments, to facilitate the development and assessment of algorithms for this use case. To this end, we developed a simulation framework dedicated to the evaluation of SLAM and routing algorithms under conditions representative of polar shipping routes. Distinct from previous work, our focus on polar shipping routes requires consideration of unique operational challenges. The dynamic environment, characterized by fluctuating ice formations, requires robust object recognition, trajectory prediction, and dynamic re-planning capabilities. Moreover, integrating multiple sensor modalities, such as sonar, LiDAR, and cameras [7], ensures comprehensive environmental perception and real-time adaptability.

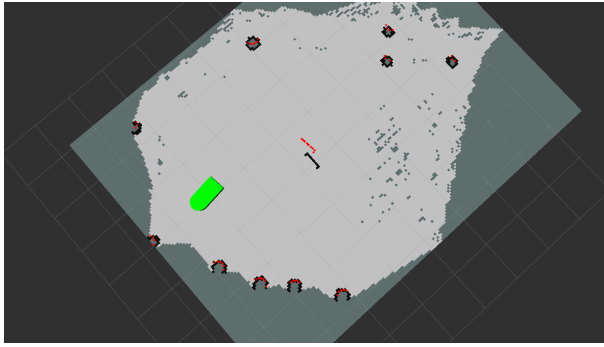


Fig. 1. SLAM environment, consisting of the autonomous vehicle and obstacles.

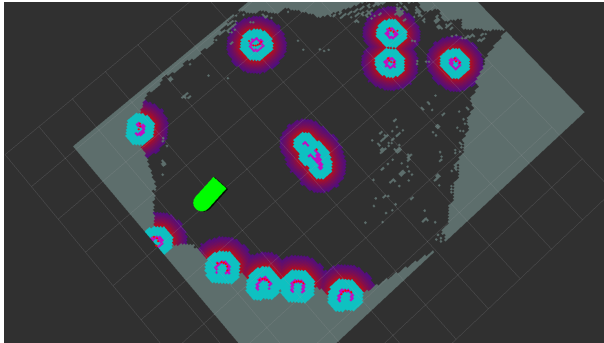


Fig. 2. Generated global cost map, which can be used for route planning.

II. METHODS

Our framework is built on Gazebo [8], a high-fidelity simulator extensively used in robotics and autonomous driving research which offers a robust, user-friendly, and extensible platform. In contrast to highly specialized simulators (e.g., proprietary systems like Kongsberg K-Sim or research prototypes such as [9]), our open-source solution is designed for ease of use and extendability. It leverages the extensive community familiarity with Gazebo and its existing ecosystem, thereby accelerating the integration of emerging methodologies. In the following, we give an overview of the platform and environment as well as currently available sensor configurations.

A. Platform Overview

The Gazebo environment (see figure 1) was built with a variety of static elements that differ in color, shape, and visibility. These elements were specifically chosen to test the full range of our sensors' capabilities. The goal was to see how well the sensors could detect objects with different visual characteristics — for example, comparing how a light-colored, low-contrast object is sensed versus a bright, high-contrast one. A good example is the construction cone, which has a strong, bright orange color and no transparent areas. In addition, we designed and built our own custom vessel, inspired by the general design of a cargo ship, but simplified for simulation purposes. Its primary purpose is to carry multiple sensors. The vessel is equipped with two rear propellers that allow it to move through the simulated environment like a ship.

The physics implementations are mainly focusing on the movement and orientation of the ship, water effects, such as buoyancy, drifting and waves are not implemented, however the propellers do mimic the movement of a real life vessel. These water concerning physics are due to be implemented. After having researched the best sensors used for object detection, spatial awareness, environmental mapping and localization, we selected 2D LiDAR, 3D LiDAR, RGBD camera (depth camera), and RGB stereo camera. In the simulated framework, all of the aforementioned sensors have been mounted at the vessel's bow, near each other, for the best forward sight. In our application, this is critical for path planning and obstacle detection. Because detecting as well as avoiding ice blocks encountered during forward motion is the primary focus, rear-mounted sensors were deemed unnecessary throughout this study. Furthermore, front-facing sensors are intended to anticipate the presence of lateral obstacles up ahead, so they then allow for trajectory adjustments prior to when collision risk arises [10].

B. Sensor Configuration

1) *2D LiDAR*: The 2D LiDAR sensor was included in our evaluation due to its widespread use in many SLAM-based algorithms. In our setup, the sensor was mounted in such way that the emitted laser beams remain parallel to the water surface, as this enables a horizontal scanning plane. The setup allows about 270 to 300 degrees of view surrounding the vessel. It extensively covers the environment on account of this configuration.

In order to test the system, we first manually steered the vessel to create an initial map of the environment. This map was then saved and utilized during the localization process [11]. While 2D SLAM algorithms are known for their flexibility and consistent performance in variety of environments [12], they might not be the most suitable in this case due to complex environmental elements and a potentially small number of data.

2) *3D LiDAR*: Developing the 3D LiDAR system evaluation based on the achieved results from the 2D LiDAR, which follows the same sensing principle but provides a more comprehensive spatial understanding [13]. Being mounted in a similar position as the 2D LiDAR, i.e., at the bow of the ship, allowing it to see what is ahead, for the consistency of the information. However, providing the spatial resolution in multiple layers, unlike the 2D LiDAR, allowing the detection of obstacles, which may not be visible in one horizontal scan.

3) *RGBD Camera*: An RGBD camera is a depth-sensing device that combines standard RGB imaging with depth information, enabling it to perceive both color and distance in the environment. This type of sensor performs reliably under both low and high visual fidelity conditions, making it suitable for a wide range of operational environments.

Similar to the 3D LiDAR, the RGBD camera generates a 3D representation of the surroundings [14]. However, it typically produces fewer localization points, as it selects only the most relevant features for mapping and pose estimation [15]. While these selected points are generally accurate and

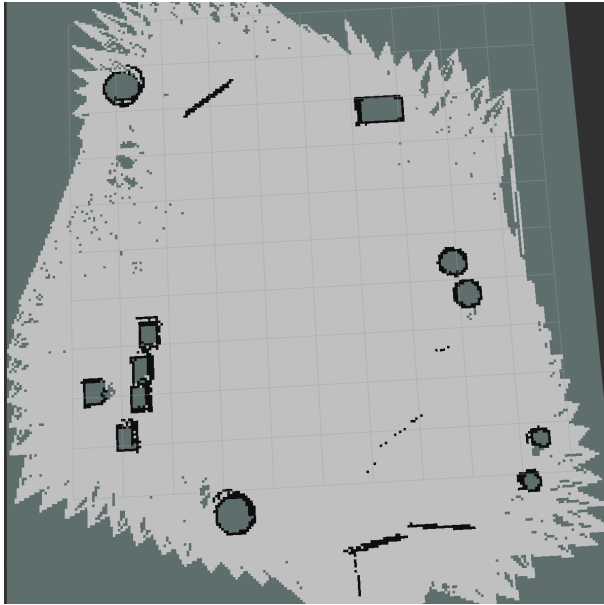


Fig. 3. Mapped the world with 2D LiDAR.

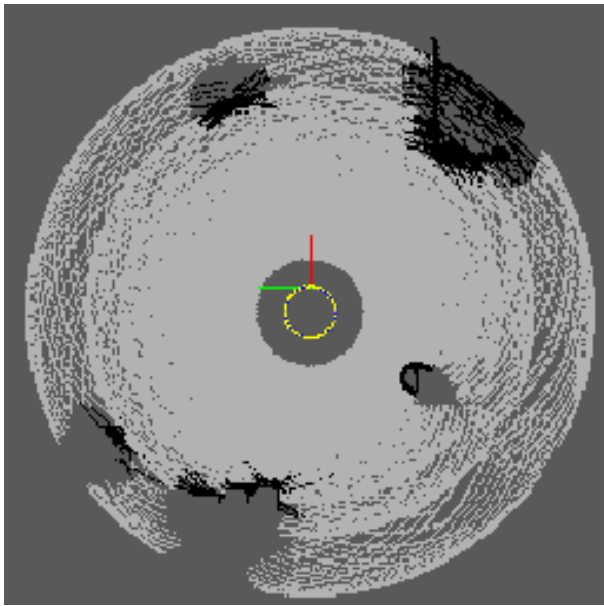


Fig. 4. Created a compressed 2D map out of the 3D LiDAR map.

sufficient for short-term localization tasks, prolonged mapping sessions often result in accumulated drift. This occurs due to the relatively limited field of view, lower range, and increased exposure to environmental factors such as lighting alterations and reflective surfaces, which can degrade depth accuracy and consistency over time.

4) *RGB Stereo Camera*: While most autonomous vehicles today rely heavily on monocular cameras for perception, this approach is not well-suited for aquatic environments, where depth estimation from a single image is unreliable due to the lack of consistent visual cues and surface features. To address this limitation, we opted to use an RGB stereo camera setup.

A stereo camera [16] consists of two calibrated cameras positioned at a fixed distance (baseline) from each other

on either side of a central axis, both oriented in the same direction. By capturing synchronized images [17] from two slightly different viewpoints, the system can compute depth information through stereo triangulation. This enables the accurate reconstruction of a 3D scene [18] and the estimation of object distances, making it a viable alternative for water surface-level depth sensing where active sensors may face limitations.

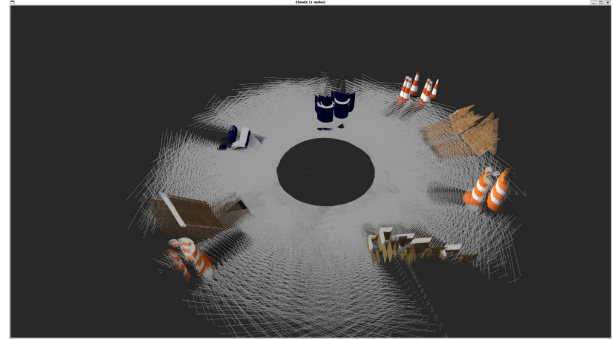


Fig. 5. Map created using the RGBD Camera.

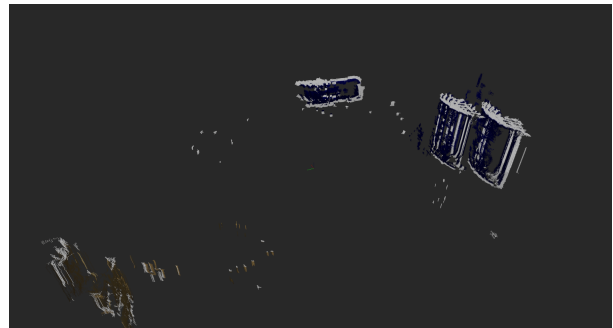


Fig. 6. Stereo Camera mapping result.

III. EXPERIMENTS

In this section, we present the performance evaluation of the performance of various sensor configurations used for SLAM in a simulated environment. We focus on comparing 2D and 3D LiDAR systems, as well as RGB and RGBD cameras, in terms of their mapping accuracy, localization reliability, and computational efficiency. These experiments aim to highlight the trade-offs between different sensor types and identify their strengths and limitations in practical scenarios.

A. 2D and 3D LiDAR Overlay

The mapping process of 3D LiDAR closely mirrors that of the 2D LiDAR, but results in significantly larger data files due to the higher dimensionality and resolution. The generated 3D maps provide an almost realistic reconstruction of the environment, offering a high level of detail and accuracy. In favorable environmental conditions, the localization performance using 3D SLAM [19] is expected to be highly precise [20]. However, this increased accuracy comes at the cost of greater computational and energy demands, making the

system less efficient compared to the 2D LiDAR, particularly in resource-constrained scenarios.

Since the 3D LiDAR can be regarded as an enhanced extension of the 2D LiDAR, a direct comparison [21] between the two was produced. To facilitate this, we generated a compressed 2D projection of the 3D LiDAR-based map, allowing us to visually compare the outputs side by side. The results (see figures 3 and 4) indicate that the 3D LiDAR map exhibits significantly higher accuracy in both object highlighting and spatial consistency. This is also reflected in the improved performance during the localization phase, where objects appear well-aligned and drift is minimal or non-existent.

In contrast, the 2D LiDAR map shows a slightly higher degree of drift, which, although still within acceptable limits for many SLAM applications, results in less precise environmental representation. Nevertheless, with the addition of a costmap (see figure 2), the 2D LiDAR system can still achieve reliable obstacle avoidance and path planning. However, when directly compared to the 3D LiDAR output, its overall performance is noticeably inferior in terms of mapping fidelity and localization stability [22].

B. RGB and RGBD Camera Comparison

The mapping process using the stereo camera during the mapping process showed promising performance in reconstructing the environment. However, the system struggled during the localization phase, as it failed to consistently identify reliable feature points for pose estimation (see figures 6 and 5 for visual example). This limitation is largely due to the extended distances typically encountered in aquatic environments, which exceed the optimal operating range of stereo vision systems.

Stereo cameras generally perform best at short to medium ranges—typically within 1 to 10 meters—where there is sufficient disparity between the left and right images to calculate depth accurately. Beyond this range, especially in open water scenarios, the disparity becomes too small to resolve, resulting in poor depth estimation and unreliable localization. As such, while stereo vision can complement other sensors in close-range tasks, it is not ideal as a primary sensing modality for long-range perception on waterborne platforms.

C. Odometry Challenges during Tuning

After all sensors demonstrated a functioning mapping process, we observed that some static elements did not consistently appear in their expected positions within the generated maps. To further investigate this discrepancy, we utilized the Transform system in ROS. The Robot Operating System 2 (ROS2) is an open-source framework widely used in robotics for building distributed and modular robot software; our implementation is available as an open-source repository [23]. The Transform system maintains the spatial relationships between coordinate frames over time, allowing the system to track how objects and sensors move relative to each other. This dynamic transformation tree (TF tree) is essential for tasks such as localization, navigation, and sensor fusion.

Upon analyzing the TF (transform) data in ROS 2—which tracks and maintains the spatial relationships between coordinate frames during runtime—we observed a gradual divergence between the vessel's estimated position and its actual simulated location as it navigated the environment. This phenomenon, known as odometry drift or odometry shift [24], reflects the cumulative error inherent in relative motion estimation systems over time.

This drift, though not always visible during real-time operation, becomes increasingly apparent in the final mapping output. Manifestations include spatial misalignments, distorted object representations, and temporal inconsistencies within the generated maps. The root cause was traced to odometric drift [25] [26], which significantly impacted localization fidelity and map consistency. Identifying and mitigating this issue was therefore essential to maintaining the overall robustness and accuracy of the SLAM process.

Sensor tuning proved critical for minimizing this drift and achieving high-quality mapping outcomes. Each sensor required environment-specific parameter adjustments to optimize performance. To evaluate odometric stability, we employed a simple but effective method (to our knowledge, original): instead of navigating the vessel through the environment, we rotated it in place by turning its bow in a circular motion. If the resulting trajectory resembled a clean, closed circle, we considered the odometry to be well-calibrated. In contrast, irregular or distorted circular paths indicated significant drift, which was typically accompanied by poorly defined environmental features in the generated map see Figure 7 for comparison between correct and failed odometry.

During testing, a primary focus was ensuring the vessel could execute a near-perfect circular motion, as this directly correlated with accurate localization performance. The closer the vessel's path approximated a true circle, the more reliable the localization phase was expected to be.

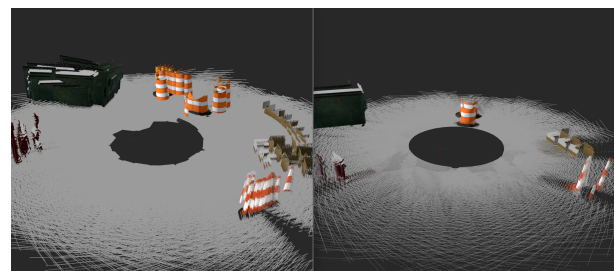


Fig. 7. Comparison between two mapping processes odometric visuals.

IV. DISCUSSION AND CONCLUSION

We evaluated the four most commonly used sensor types in SLAM and autonomous navigation: 2D LiDAR, 3D LiDAR, RGBD cameras, and stereo fisheye cameras. These categories were chosen due to their widespread commercial availability and frequent use in autonomous vehicles. Furthermore, their proven effectiveness makes them suitable candidates for maritime applications, particularly for navigation along polar sea routes used in modern cargo shipping.

The physical characteristics of large maritime vessels introduce unique navigational challenges. These ships typically are hard to steer and have limited reverse capability, making agile maneuvering—especially evasive actions—difficult to perform. Furthermore, environmental factors such as weather conditions can significantly degrade sensor fidelity. Given the unpredictability and severity of such conditions in maritime and polar environments, it is crucial to design a perception system capable of robust operation across a wide range of scenarios.

The water surface and above water existing objects are constantly moving because of the waters dynamics and wind conditions, in some cases more than others. The creation of such SLAM system would be optimal for predicting all kind of obstacles, the most common being on the polar routes - ice-blocks. These ice obstacles size, location and speed are hard to predict, furthermore their depth in water is also highly concerning.

We tested all four sensors in a static environment (the first scenario) to evaluate their strengths and weaknesses. The results showed that some sensors are better suited for short-range tasks, such as the stereo camera for docking. Others, like the RGB-D camera, perform well in low-light conditions and can help predict object orientation. The LiDAR sensor, meanwhile, is cost-efficient and highly reliable for monitoring dynamic, above-water environments.

Even though we tested the system in degraded visual conditions, enhancements can still be made - the best idea would be testing the sensors functionality on real-life data.

The framework introduced in this paper initiates the development for the next generation of fully autonomous vessels, capable of navigating the dynamic and challenging conditions of the Polar regions with precision and efficiency. As an initial step into this evolving field, this research paves the way for future advancements, including the integration of Artificial Intelligence, Mixed Reality-based Object Detection, various SLAM solutions, and cutting-edge computer vision techniques to enhance situational awareness, obstacle detection—particularly the avoidance of moving ice blocks—and autonomous decision-making in extreme maritime environments. Research in this field has the potential to push the boundaries of autonomous navigation, enabling environmentally friendly, secure, and rapid maritime transport in these increasingly accessible but highly demanding regions.

REFERENCES

- [1] H. Schøyen and S. Bråthen, “The northern sea route versus the suez canal: Cases from bulk shipping,” *Journal of Transport Geography*, vol. 19, no. 4, pp. 977–983, 2011.
- [2] J. D. Smith, S. Hall, G. Coombs, *et al.*, “Autonomous passage planning for a polar vessel,” *arXiv preprint arXiv:2209.02389*, 2022.
- [3] C. Stachniss, J. J. Leonard, and S. Thrun, “Simultaneous localization and mapping,” *Springer handbook of robotics*, pp. 1153–1176, 2016.
- [4] D. Van Nam and K. Gon-Woo, “Solid-state lidar based-slam: A concise review and application,” in *2021 IEEE International Conference on Big Data and Smart Computing (BigComp)*, IEEE, 2021, pp. 302–305.
- [5] G. Sibul and J. G. Jin, “Evaluating the feasibility of combined use of the northern sea route and the suez canal route considering ice parameters,” *Transportation Research Part A: Policy and Practice*, vol. 147, pp. 350–369, 2021.
- [6] K.-I. Benta and D.-C. Deselnicu, “The opportunity of a benchmarking tool for obstacle avoidance in autonomous shipping,” in *Proceedings of The International Maritime Transport and Logistics Conference (MARLOG14)*, Alexandria, Egypt, Feb. 2025, pp. 497–508, ISBN: 978-977-85808-8-4.
- [7] Q. Li, J. P. Queralta, T. N. Gia, Z. Zou, and T. Westerlund, “Multi-sensor fusion for navigation and mapping in autonomous vehicles: Accurate localization in urban environments,” *Unmanned Systems*, vol. 8, no. 03, pp. 229–237, 2020.
- [8] N. Koenig and A. Howard, “Design and use paradigms for gazebo, an open-source multi-robot simulator,” in *2004 IEEE/RSJ international conference on intelligent robots and systems (IROS)(IEEE Cat. No. 04CH37566)*, Ieee, vol. 3, 2004, pp. 2149–2154.
- [9] M. Minami, M. Kobayashi, K. Hikida, and K. Kokubun, “Development of the comprehensive simulation system for autonomous ships,” in *Journal of Physics: Conference Series*, IOP Publishing, vol. 2311, 2022, p. 012012.
- [10] T. Bailey and H. Durrant-Whyte, “Simultaneous localization and mapping (slam): Part ii,” *IEEE Robotics & Automation Magazine*, vol. 13, no. 3, pp. 108–117, 2006. DOI: 10.1109/MRA.2006.1678144.
- [11] M. G. Ocando, N. Certad, S. Alvarado, and Á. Terrones, “Autonomous 2d slam and 3d mapping of an environment using a single 2d lidar and ros,” in *2017 Latin American Robotics Symposium (LARS) and 2017 Brazilian Symposium on Robotics (SBR)*, 2017, pp. 1–6. DOI: 10.1109/SBR-LARS-R.2017.8215333.
- [12] V. Vaquero, E. Repiso, and A. Sanfeliu, “Robust and real-time detection and tracking of moving objects with minimum 2d lidar information to advance autonomous cargo handling in ports,” *Sensors*, vol. 19, no. 1, p. 107, 2019. DOI: 10.3390/s19010107.
- [13] B. Zhou, Y. He, K. Qian, X. Ma, and X. Li, “S4-SLAM: A real-time 3d lidar slam system for ground/watersurface multi-scene outdoor applications,” *Autonomous Robots*, vol. 45, no. 1, pp. 77–98, 2021. DOI: 10.1007/s10514-020-09948-3.
- [14] W. Xie, P. X. Liu, and M. Zheng, “Moving object segmentation and detection for robust rgbd-slam in dynamic environments,” *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1–8, 2021. DOI: 10.1109/TIM.2020.3026803.
- [15] Y. Liu, M. Xu, G. Jiang, *et al.*, “Target localization in local dense mapping using rgbd slam and object de-

- tection,” *Concurrency and Computation: Practice and Experience*, 2021. DOI: 10.1002/cpe.6655.
- [16] T. Naruse, T. Kaneko, A. Yamashita, and H. Asama, “3-d measurement of objects inwater using fish-eye stereo camera,” in *2012 19th IEEE International Conference on Image Processing*, 2012, pp. 2773–2776. DOI: 10.1109/ICIP.2012.6467474.
- [17] G. Kocak, S. Yamamoto, and T. Hashimoto, “Analyzing influence of ship movements on stereo camera system set-up on board ship,” vol. 47, no. 6, pp. 888–895, 2012. DOI: 10.5988/jime.47.888.
- [18] Y. Nomura, S. Yamamoto, and T. Hashimoto, “Study of 3d measurement of ships using dense stereo vision: Towards application in automatic berthing systems,” *Journal of Marine Science and Technology*, vol. 26, no. 2, pp. 573–581, 2021. DOI: 10.1007/s00773-020-00761-2.
- [19] X. Xu, L. Zhang, J. Yang, *et al.*, “A review of multi-sensor fusion slam systems based on 3d lidar,” *Remote Sensing*, vol. 14, no. 12, 2022, ISSN: 2072-4292.
- [20] E. Aydemir, N. Fetic, and M. Unel, “H-vlo: Hybrid lidar-camera fusion for self-supervised odometry,” in *2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2022, pp. 3302–3307. DOI: 10.1109/IROS47612.2022.9981111.
- [21] S. Jiang, S. Wang, Z. Yi, M. Zhang, and X. Lv, “Autonomous navigation system of greenhouse mobile robot based on 3d lidar and 2d lidar slam,” *Frontiers in Plant Science*, vol. 13, 2022. DOI: 10.3389/fpls.2022.815218.
- [22] R. Sawada and K. Hirata, “Mapping and localization for autonomous ship using lidar slam on the sea,” *Journal of Marine Science and Technology*, vol. 28, pp. 410–421, 2023. DOI: 10.1007/s00773-023-00931-y.
- [23] K. Orban, *Polar shipping sensors*, <https://github.com/Klaraaorban/Polar-Shipping-Sensors>, GitHub repository, 2025.
- [24] H. Liu, R. Jiang, W. Hu, and S. Wang, “Navigational drift analysis for visual odometry,” *Computing and Informatics*, vol. 33, no. 3, pp. 685–706, 2015.
- [25] P. Kim, B. Coltin, and H. J. Kim, “Low-drift visual odometry in structured environments by decoupling rotational and translational motion,” in *2018 IEEE International Conference on Robotics and Automation (ICRA)*, 2018, pp. 7247–7253. DOI: 10.1109/ICRA.2018.8463207.
- [26] L. R. Agostinho, N. M. Ricardo, M. I. Pereira, A. Hiolle, and A. M. Pinto, “A practical survey on visual odometry for autonomous driving in challenging scenarios and conditions,” *IEEE Access*, vol. 10, pp. 72 182–72 205, 2022. DOI: 10.1109/ACCESS.2022.3188990.