Preventing Collisions with Critical Port Infrastructure

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Abstract. Port areas present significant challenges for the current shipping industry and in future for autonomous vessels. Accident and near-miss rates are high due to confined spaces and difficult environmental conditions. This leads accidents and to inoperability and loss of critical infrastructure. We present safe onshore automation islands to support navigators with additional information independently of the vessel's equipment. We first use IHPC's near-miss case detection system to identify critical areas, where navigational support is required. Then a lidar-based automation island is optimized to guarantee support during critical maneuvers. For this a sensor coverage optimization algorithm and novel fitness function is presented to improve the sensor system's performance for critical trajectories. The fitness function measures the contiguous recognized contour of the vessels hull. With this we are able to perceive 86% of the lateral vessel hull during all critical maneuvers.

1. Introduction

While severe maritime accidents are infrequent, minor accidents or near-misses are occurring with increasing frequency. [1]. The consequences are serious: in addition to economic damage to the ship and infrastructure, they can result in environmental damage due to leaking oil or personal injury. In 2024, a dredger collided with a stationary bunker vessel in Singapore's port waters, spilling about 400 tons of oil and causing widespread slicks across multiple shorelines [2], while mid 2025 an oil tanker collided with an offshore supply vessel entering Cuxhaven Harbor in Germany, leaking approximately six cubic meters of marine fuel [3]. According to reports of protection and indemnity clubs (P&I) most accidents occur with static infrastructure [4]. It is assumed that a large number of such cases remain unreported, as most minor damages are either not reported or go unnoticed. Collisions with infrastructure occur in confined spaces inside ports that are navigationally challenging, such as port or lock entrances. Adverse environmental conditions (e.g. wind and currents) can also increase the frequency of incidents. The cause is often human error due to insufficient situational awareness when monitoring the vessel's immediate vicinity [5]. For example, when entering port areas, visibility from the vessel's side may be limited, as port infrastructure can interfere with or obscure sensors such as radar and cameras. Automation islands are geographically limited and shore-based assistance systems that support certain automation processes [6]. However, designing such a sensor system is challenging. Since automation islands usually include perception components, it must be ensured that all objects can be detected under all relevant influencing conditions. Thus, the system must be specifically tailored to the location, weather conditions and navigational factors.

This paper presents a concept for safe shore-based maritime automation islands to support navigators when navigating in confined areas. The work builds on the existing berthing assistance system SmartKai[1] developed at the German Aerospace Center. Besides providing environmental measurements, the shore-based system supports navigators with high-range LiDAR sensors (up to 300m under adverse weather conditions), to determine distance and speed information in relation to static infrastructure [7]. Within this paper, large-scale AIS-based modelling of berthing behaviour and the analysis of vessel trajectories passing near static infrastructure are first conducted to characterise vessel–infrastructure interaction patterns in confined port areas. Building on these results, a data mining task using IHPC's near-miss case detection system is then carried out to identify unreported near-miss or minor incident cases and to provide insights for pinpointing critical areas within a harbour. Through this combined analysis, locations with a high likelihood of incidents involving static infrastructure are identified. Next, the analysis examines the geographical area requiring assistance and how shore-based sensors can fully cover it. The goal is to find the optimal sensor setup using a coverage optimization algorithm. For this we conduct an experiment using a LiDAR sensor simulation, to examine different sensor configurations and locations, leading to a trade-off analysis between the proposed setup and alternatives.

2. State of the art

The performance and safety of optical methods depend on the perception area of the sensor technology. Here, objects should be detected in their entirety to enable object classification or feature extraction. Optimization of LiDAR sensor placement and orientation is therefore a critical component in achieving high perception reliability.

Early works perform on-vehicle sensor optimization to improve object detection. Berens et al. propose one of the earliest systematic frameworks for optimizing vehicle-mounted LiDAR configurations using a genetic algorithm [8]. Their work formulates sensor placement as a combinatorial optimization problem, including LiDAR position, orientation, and number of sensors. Coverage quality is evaluated through a simulation-based metric that measures object visibility and point cloud density across relevant regions of interest around the vehicle. Kim & Park formalized the multi-LiDAR placement problem as a geometric optimization task minimizing dead zones and maximizing point cloud resolution [9]. Their occupancy-grid approach established a baseline for coverage analysis. A similar approach was introduced by Hafemann & Hahn, who create a coverage analysis framework across multiple sensor modalities [10]. In another publication, they develop the Omni-LiDAR Evaluation Score for optimizing sensor placement, measuring uniformity, coverage, and spatial distribution of point clouds in comparison to a reference target [11]. He et al. integrate joint beam distribution with physical sensor placement, leveraging optimization algorithms to align LiDAR scan patterns with vehicle motion dynamics based on multi-view occupation grids [12].

The transition from dynamic on-vehicle to static LiDAR networks introduce additional geometric and occlusion constraints. Jin et al. introduce an entropy-guided visibility metric, improving computational efficiency in large-scale simulations [13]. They reduce complex LiDAR

[1] DLR - SmartKai Research ProjectDLR - SmartKai Research Project

mounting placement into a simpler parameter optimization problem. Li et al. (2024) optimize LiDAR–camera co-placement for better data fusion by optimizing the sensor placement for specific detection algorithms [14]. Jiang et al. propose an entropy-based surrogate metric to evaluate object detection performance for different LiDAR configurations, while prioritizing critical traffic areas [15]. Steger et al. demonstrate coverage optimization principles for shore-mounted sensors, applicable to maritime autonomy [6].

Adopting methods to this paper`s use case, we face some unique challenges that are not present in other domains. As opposed to vehicle-mounted systems, the sensor setup is mounted on shore infrastructure and thus observers a static environment. Thus, sensor coverage can be optimized for a limited geographical area with minimal influencing factors as opposed to vehicle mounted systems. In contrast to related work, we do not aim to optimize the sensor setup to cover a specific area, but for critical maneuvers. Thus, using historic trajectories enables optimization for specific maneuvers and vessel characteristics (e.g. dimensions). Additionally, especially in maritime environments, unique environmental challenges that influence the sensors performance like rain, snow, or fog must be considered. Optimization can therefore be done for unique environmental effects for the known area.

3. Shore-based automation islands for preventing port infrastructure collisions

The automated provision of information based on infrastructure-based sensors is already a well-established way of adding safety to automation processes. Ongoing standardization efforts [16, 17] and studies proving advantages of infrastructure-based sensors [18] further solidify the movement away from vehicle centric sensor systems to distributed sensor systems in the automotive domain. Historically cooperative approaches like AIS or shore-based Radar stations connected to VTS stations are common in the maritime domain. However, each of these approaches present technical and operational limitations. AIS is only mandatory for vessels of 300 Gross tonnage and above according to SOLAS. Shore-based radar stations are able to relay information about the current traffic situation in their detection zone, however this information is mainly provided as spoken word via VHF. While scientific research already indicates the importance of shore-based systems in the maritime domain, content is still scarce. ISO23860:2021 defines the concept of Local Sensor Systems (LSS) as part of a Maritime autonomous surface ship (MASS). However, concrete concepts for implementation of such a system are still missing.

Based on concepts of the automotive domain, the goal of the Island of Automation is to create an area where local information is forwarded to connected vehicles operating in the area. This way the sensor system can be tailored to the local requirements and costive sensors can be used more efficiently compared to the currently vessel centric sensor systems. Conceptually the Island of Automation is comprised of three levels: distributed sensor nodes monitor the area of interest and report measurements to a central backend via communication nodes. Reported information is fused in the backend to achieve a more complete situational picture. Relevant information is the distributed to vessels operating inside the area. However, key challenges still remain to be solved. One of these challenges is the determination of relevant areas of interest and how to ensure that these systems are safe under all condition. As misinformation or false data might lead to wrong decisions, is must be ensured that the sensor system is able to fully perceive the vessels.

To solve these challenges, Figure 1 visualizes the overall concept of this paper. We use large-scale historic AIS data combined with information about the port infrastructure. In the first step, we determine critical port areas. These are characterized by areas where vessels perform dangerous maneuvers (e.g. sailing close to harbor walls or performing unusual maneuvers). The output of this step is vessel trajectories combined with criticality measures. This information is used for the last step to optimize the sensor setup to support these critical maneuvers.

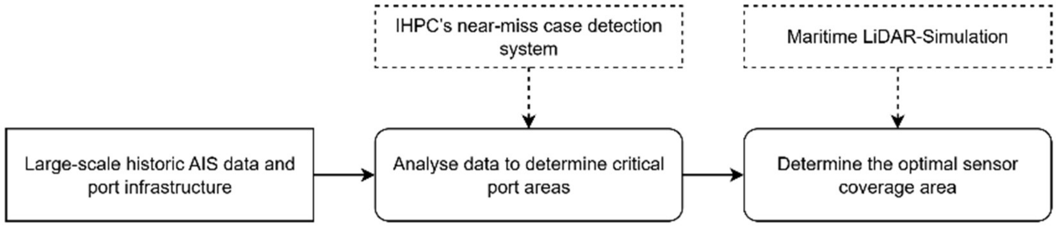

Figure 1 Concept for preventing collisions with critical port infrastructure by optimizing sensor setups

The IHPCs near-miss case detection system forms a core component of the proposed framework, enabling the automated identification of high-risk interactions between vessels and port infrastructure. Near-miss cases represent precursors to potential accidents where vessels execute precarious maneuvers close to harbor walls, berths, or other fixed structures. By leveraging large-scale historic AIS data alongside port infrastructure details, such as quay layouts, this system identifies risk behaviors based on physical momentum and distance and extracts the corresponding trajectories. Through statistical analysis, it ultimately outputs targeted regions and targets as inputs for optimizing sensor placements.

Conceptually, near-miss detection employs a multi-layered methodology grounded in spatiotemporal analysis and risk thresholding. First, vessel trajectories are preprocessed through quality control and data cleaning procedures. Subsequently, sailing-past and berthing events are identified based on distance thresholds, vessel speed profiles, and heading-change patterns. Further, anomalous vessel maneuvers, such as excessively urgent evasions or high-speed contacts with shore-based structures, are detected using data-driven models. Finally, these near-misses are quantified as a proportion relative to all normal behaviors (i.e. sailing-past and berthing events), yielding numerical indicators of collision-prone regions and targets, as well as those most susceptible to cumulative damage over time.

Sensor Coverage Optimization

In order to continuously support vessels during critical manoeuvres, it must be ensured that the sensors perceive vessels under all conditions. For this we optimize sensor setups for specific vessel trajectories and validate this using a maritime LiDAR simulation. This simulation is able to simulate different vessels, LiDAR sensors and environmental conditions influencing the detection performance. Thus, this is considered as an optimization problem including the variables “sensor position” and “orientation”. These variables may be subject to additional constraints (e.g., mounting locations on the infrastructure or shading effects), depending on the location. It can be repeated for different sensors and configurations. We use an evolutionary algorithm as the optimization algorithm. Each chromosome of a LiDAR sensor consists of the position (P_X, P_Y, P_Z) and the orientation (O_X, O_Y, O_Z). During optimization, the most promising elements are mutated and combined. For the implementation we use the PyGAD python library for genetic algorithms [19]. To apply this algorithm, a fitness function is required. Three essential aspects of LiDAR perception data quality must be taken into account when defining a fitness function for the algorithm: uniformity, coverage, spatial distribution [11]. With uniformity the point cloud distribution is reflected. The uniformity, however, does not consider the effects of coverage. Coverage relates to the ratio between the covered surface and the total surface area of a target.

Finally, the spatial distribution of clusters on the target is measured. We attempt to consider these aspects by calculating the contiguous recognized contour of the vessels hull.

To explain this in more detail, Figure 2 shows the point distribution of a single LiDAR sensor on a vessel. Parts of the ship that are close to the sensor are hit with a high density of laser beams. When vessel parts are in an acute angle to beams, the point density decreases. At a low density, it cannot be assumed that the points still belong to the target. Therefore, these points may be erroneous or noise. Density can additionally be influenced by environmental factors. For example, in the event of rain or snow, some points can already be filtered at the sensor level.

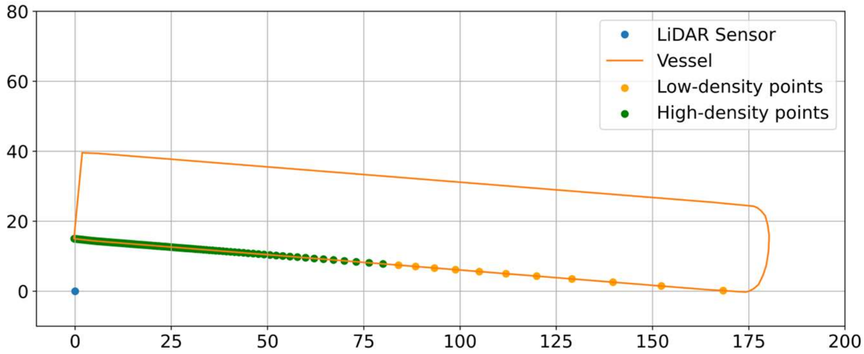

Figure 2 Spatial distribution of LiDAR points on a target vessel. Higher density of points near the sensor (red), lower density in areas with an acute angle between target and sensor (yellow).

To apply this optimization function for unordered point clouds, we first employ DBScan (Density-Based Spatial Clustering of Applications with Noise) to determine connected groups of points [20]. This algorithm uses the reachability between points to check for arbitrary formed clusters. Clusters form lines for the outer hull of the vessel. Afterward, a modified curve detection algorithm is applied on each cluster [21], based on [22]. The algorithm first reduces a noisy 3-D point cloud to its local "center line", by searching for neighborhood points and projecting these onto the first principal component. Then singular value decomposition (SVD) is applied to obtain the dominant direction and to store the projected points along with their regression lines. The resulting points are ordered into a continuous trajectory. Starting from an arbitrary seed, it walks forward and backward along each point's local regression direction, repeatedly searching for a small sphere for the next point that best aligns with the tangent. The two directional walks are concatenated to yield an ordered list that traces the underlying curve. The fitness function is then calculated using the total length of all lines of each cluster. The optimization algorithm thus optimizes the sensors observation area to perceive as much of the vessels hull as possible.

4. Experiment

To test the proposed approach, we perform an experiment using historical AIS data. The initial aim of the experiment is to identify critical points in the port area for which an automation island can be optimized. This is followed by the simulative optimization process, in which different configurations and environmental conditions are compared. A detailed analysis of the results of the proposed optimization function is then carried out.

Detection of critical port areas

Historical AIS data from the Cuxhaven port area was used for the experiment. Infrastructure elements were obtained from nautical chart servers. This data serves as input for the IHPC near-miss case detection system. The search focuses on larger transport ships (e.g., RoRo, container, bulk cargo), as well as smaller ships from commercial shipping (e.g., fishing boats, tugs, pilot boats). Smaller ships, especially those from the recreational boating sector, were not considered, as the potential for damage was assessed as low.

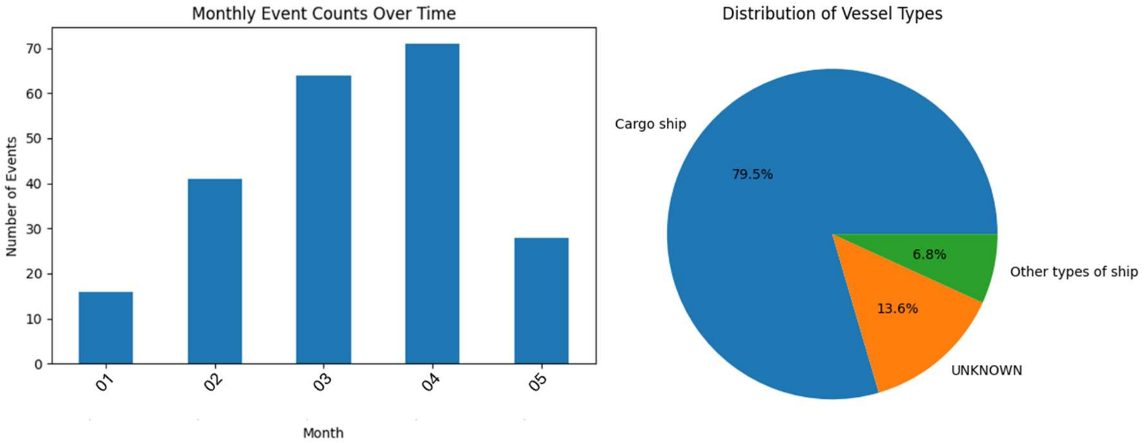

Figure 3 Related statistics of detected berthing behaviors

Berth ID	Detected Berthing	Near-miss candidate	Rate of near-
1	41	2	0.049
2	74	2	0.027
3	37	6	**0.162**
4	29	2	0.068
5	19	1	0.052
6	20	0	0
total	220	13	0.059

Table 1 Detection results

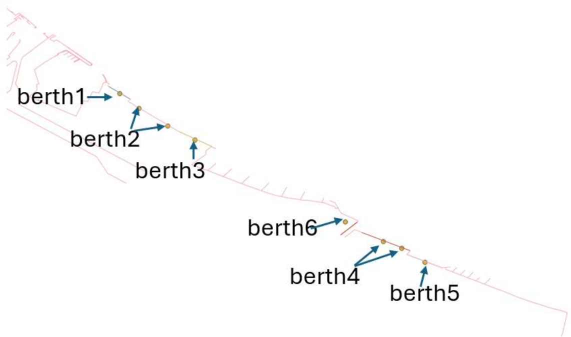

Figure 4 Berth numbering and position

We preprocessed four months of pseudonymized and partly randomized raw AIS data (we maintained the monthly distribution) and conducted a berth behavior analysis and detection. All 220 berthing behaviors of the original data set were detected. Related statistics are presented in Figure 3. The near-miss detection results are shown in Table 1. Based on the results, Berth 3 shows a noticeably higher likelihood of relatively hazardous berthing behavior, which is likely influenced more significantly by wind and current conditions. In contrast, berthing operations at Berth 6 appear to be comparatively the safest.

Optimization results

Since Berth 3 has the highest likelihood of hazardous berthing maneuvers, we apply the automation island to it. We employ an optimization procedure to identify a sensor configuration that supports berthing vessels as part of a berthing assistance system. In this scenario, close-range systems are particularly relevant since the pilots and ship masters operating in Cuxhaven stated that the last 100-120m relative to the quay wall are critical for berthing maneuvers [7]. Given the safety-critical nature of the application, we consider sensors that are already deployed in vehicle assistance systems; specifically, we focus on LiDAR units originating from the autonomous driving domain in the automotive sector that are suitable for maritime use cases. These sensors typically feature a 120° horizontal field of view and an angular resolution ranging from 0.05° to 0.3°.

Using the aforementioned configuration in combination with historical maneuver data, we examine potential sensor mounting positions and optimize the number, placement, and orientation of the sensors to maximize hull visibility throughout the maneuver. In total we examined six maneuvers (see Table 1) with a variable number of sensors (1-5). We investigate the minimum number of sensors required to ensure a minimum level of safety, measured in terms of the fitness function. Figure 5 first shows the results of the optimization project in the form of statistical measures.

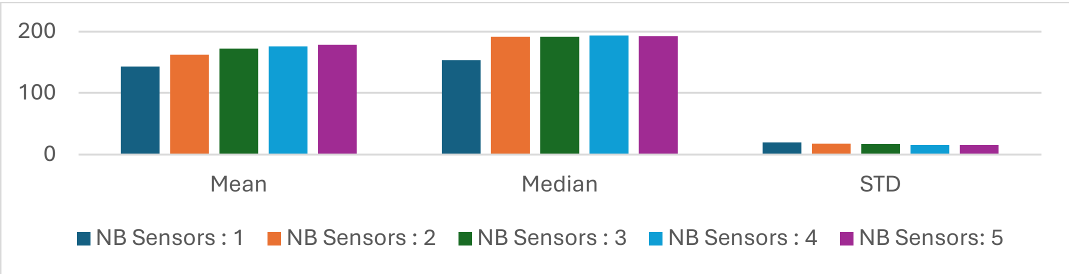

Figure 5 Comparison optimization results of different sensor setups with varying number of sensors

As expected, the fitness function increases with a higher number of sensors, as a larger area of the plant can be covered. Conversely, the standard deviation decreases with increasing numbers. The highest changes (mean, median) are recorded here between a sensor count of 1 and 3. Beyond a count of 3 sensors, the benefit of additional sensors is therefore lower. A plateau is reaches with 5 sensors as seen in the median and standard deviation measures. The ships have an average length of 200m, whereby all sensor configurations are able to perceive on average a large amount of the vessels lateral hull. With three sensors we are able to perceive 86% on average of the lateral hull of all vessels.

We also investigated how the sensors are positioned and oriented (Figure 6). We found that there are similarities in both positioning and orientation with an increasing number of sensors. There appear to be sensor positioning areas in the 50-100m and 150-200m ranges. The reason for this is that the vessels are mainly positioned in the range between 100 and 200m during their approach. At this quay, there is no loading bridge or similar facility. Thus the ~200m long vessels have a large area available for berthing. It is also noticeable that 50% of the sensors are tilted to the left and 50% to the right. As all vessels approach the quay from the left side, the sensors oriented to the left detect the ships as they approach. Thus, they are used for long-range detection.

Sensors oriented to the right detect vessels at a close range. We observed that all sensor setups continuously detect the vessels side, as this is the greatest area of the hull. Also, this is the easiest to detect, as all vessels performed berthing maneuvers with the bow tilted towards the quay. The plateau we observed for five sensors in Figure 5 can also be seen in Figure 6, as one sensor in the center is aligned with the quay wall, which does not add a benefit for the vessel perception.

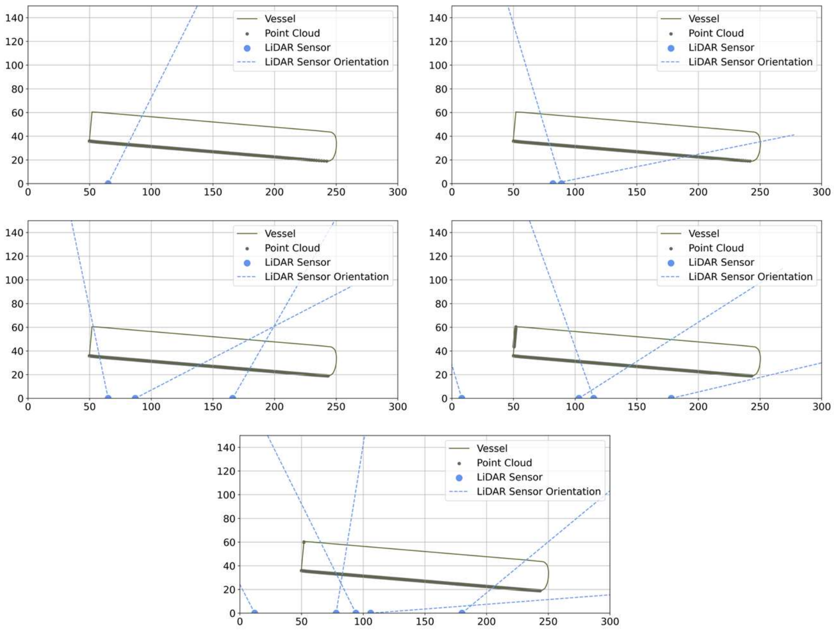

Figure 6 Optimized sensor placement for up to 5 sensors shown for an examplary RoRo vessel position. Orientation line is the center of the sensors view port of 120°.

5. Conclusion and outlook

In this paper, we presented an approach that can be used to detect critical berthing maneuvers in ports and to design a safe shore-based automation island. We presented an optimization method for positioning and orienting of LiDAR sensors, as well as a novel fitness function for measuring contiguous areas of a vessel. This function meets the quality requirements for uniformity, coverage, and spatial distribution. To verify the results, an experiment was conducted using historical data from Cuxhaven, Germany. This experiment examined critical areas in Cuxhaven and how maneuvers can be supported with an optimized sensor setup. A variable number of sensors were examined and similarities in the structures were identified. Here, an average of 86% of the ship's hull could already be captured with three LiDAR sensors.

The results are a first step in the development of safe automation islands and shore-based support for shipping. Further analysis must be carried out to improve this approach in the future. For example, it is necessary to take local environmental conditions into account in the optimization and simulation, and to consider a longer historical period. The optimization was only performed on the most critical maneuvers, although non-critical situations must also be supported in order to assist shipping. In addition, the metric presented only determines the length of the contiguously recognized areas. It does not take into account whether key points of the ships (e.g., stern, shoulder) are also recognized. We therefore plan to expand the optimization process to include the detection of specific key points in the future.

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