Enhancing Situation Awareness for Safe Maritime Navigation: Towards Using High-Resolution Electronic Navigational Charts in Highly Automated Shipping

Christopher Petersen, Fynn Pieper, Arne Bokern, Matthias Steidel

Highly automated vessel operations depend on accurate and reliable information about the vessel's surroundings. This paper addresses the challenges of ensuring maritime navigational safety, even when the integrity of Electronic Navigational Charts (ENC) is compromised and nearby obstacles become a collision risk. We propose High-Resolution Electronic Navigational Charts (HR-ENCs) as a tool to capture sensor data, combining LiDAR, radar, camera, GNSS and existing ENCs, using a loosely-coupled sensor fusion framework to assess current conditions within harbors. By accurately identifying and georeferencing maritime objects, we aim to enhance Situation Awareness (SA) and ensure safe navigation of both manned and unmanned vessels. By focusing on the detection of discrepancies between observed conditions and charted objects, HR-ENCs reflect current harbor conditions even when official charts are deprecated. Further, we outline the infrastructure needed to distribute HR-ENCs among maritime stakeholders, showcasing the potential of maintaining harbor-wide charts through consistent and timely updates that are available to all stakeholders. Our approach is applied to a use case in a harbor area. Therefore, we record sensor data with a research vessel and generate 3D data to compute the HR-ENCs. The results confirm the feasibility of integrating 3D measurements into navigational charts. In addition, we explore applications and challenges in using HR-ENCs beyond ENC verification, emphasizing their potential in developing Advanced Driver Assistance Systems (ADAS) for collision avoidance and precise berthing maneuvers. HR-ENCs promise to improve navigational safety, particularly in complex harbor environments, and support the advancement of highly automated maritime systems, thereby contributing to the broader adoption of autonomous maritime operations.

KEYWORDS

~ Remote operation
~ Mapping
~ Maritime navigation
~ Electronic navigational charts
~ Situation awareness

German Aerospace Center, Institute of Systems Engineering for Future Mobility, Oldenburg, Germany
e-mail: christopher.petersen@dlr.de
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1. INTRODUCTION

When looking at the current developments in academia and industry, Maritime Remote Operation seems to be a promising solution, as the shortage of skilled labor in the maritime industry persists (BIMCO and International Chamber of Shipping, 2021). Besides traditional ocean and short sea shipping, vessels that are responsible for port maintenance (e.g. dredging) are a promising use case for Maritime Remote Operations, especially when it encompasses Multi-Ship-Operations. However, when conducting Maritime Remote Operations, Situation Awareness (SA), as defined in Endsley (1995), with regards to collision avoidance becomes a crucial task for remote operators (Abilio Ramos et al., 2019). Although existing technologies like the Automatic Identification System (AIS) and radar can detect moving targets reliably, the detection of semi-stationary port objects (e.g. uncharted buoys) within Remote Operation Centers (ROC) mainly relies on camera images. Especially in narrow fairways, harbor areas or locks, comprehensive SA is essential for the safe navigation of ships. With regard to remote operations, this means that the operators must be able to reliably assess where harbor infrastructure is positioned in relation to the ship.

Existing perception technologies, such as LiDAR, cameras or radars, already enable the detection and identification of harbor objects (Thombre et al., 2022). In addition, commonly used Electronic Navigational Charts (ENC) also contain information about the type and location of objects (International Hydrographic Organization, 2017), however bringing up the question of how accurate and up-to-date this information is. An example for discrepancies between ENCs and real-world information can be seen in the Jarßum Harbor, by comparing the aerial image in Figure 1 to the ENC in Figure 2.

Figure 1. Jarßum Harbor in Emden, Satellite Image (Imagery ©2025 AeroWest, Airbus, CNES / Airbus, Maxar Technologies, Map data ©2025 GeoBasis-DE/BKG (©2009), Google)

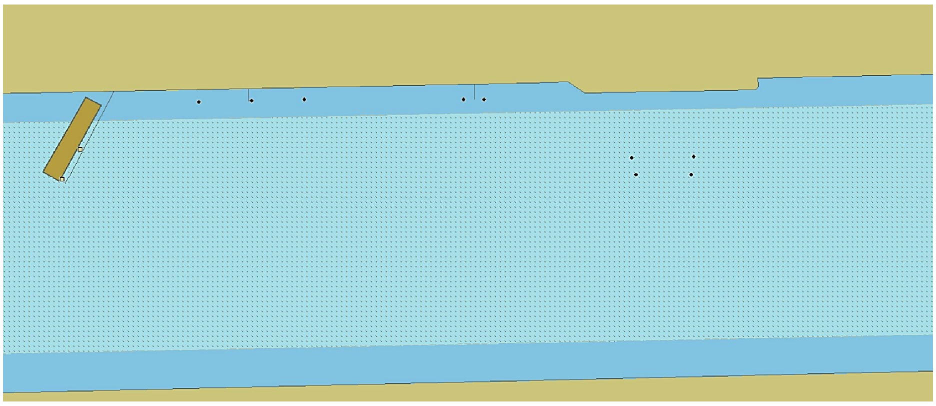

Figure 2. ENC for Jarßum Harbor (Professional+ chart data from Lloyd's Register/i4Insight in a ChartServer solution from ChartWorld.)

It is apparent that the depicted crane (blue structure on the right side in Figure 1) is not sufficiently captured in the ENC (Figure 2), as it is lacking in detail in the representation of its shape and measurements for the crane are not available. When comparing the chart data to the characteristics in the satellite image, the chart is missing out on relevant structures and only showing some of the existing mooring facilities around it. The structure on the left side is representing a movable pontoon, but while the position on the satellite image appears to be the same as in the ENC, this is not always the case due to the pontoon being able to move along the quay wall. Overall, features are not represented thoroughly and moving features are not considered at all, therefore questioning the suitability of the ENCs for precise navigation. This describes a limiting factor for future maritime navigation, when further developed and advanced autonomous systems will be in use that require a precise and accurate representation of the surrounding environment.

The challenge of inaccurate ENCs becomes even more relevant when considering regulatory developments of recent years. The International Hydrographic Organization (IHO), responsible for releasing and maintaining the ENCs, recognizes the limitations of current charts with regard to recency and level of detail, acknowledging potential issues with integration for multi-ship, remote-controlled or autonomous ship operation (International Hydrographic Organization, 2018). Det Norske Veritas (DNV) emphasizes that reliable "Remote Situational Awareness" is essential to achieve a degree of safety comparable or exceeding conventional ships (DNV GL AS, 2018). At the same time, the guidelines published by the International Maritime Organization (IMO) explicitly require that the risks arising from incomplete environmental and navigational information must be systematically analyzed and addressed during the trials of autonomous ships (International Maritime Organization, 2019). As a consequence, insufficient charts are directly linked to the regulatory requirements needed for safety assurance during navigation.

We address these challenges by our work: The idea is to combine perception technologies with ENCs in order to create, use and maintain High-Resolution Electronic Navigational Charts (HR-ENCs). Accurate and reliable charts help both remote operators and autonomous navigation systems to navigate precisely in narrow harbor waters and thus have the potential to contribute to the safeguarding of highly automated maritime systems.

In this paper, we discuss the generation and use cases of HR-ENCs, based on the problem of how SA of remote operators can be increased as well as how to improve the quality and accuracy of conventional ENCs. This also includes the challenge of integrating multiple sensor modalities from different sources to create a picture of the situation. For this, we take a look into current approaches for highly accurate environment perception in various domains, deriving a common approach from the literature that we adjust for our problem in the maritime domain. Afterwards, we specify technology needed for sufficient environment perception in harbor areas, while our work focuses on perceiving the environment above the water surface. Further, we lay out a communication infrastructure for the use of distributed HR-ENCs by sharing data between vessels. An example is given for a scenario based on remotely controlled vessels. Further, we describe a use case in the Jarßum Harbor, where a measuring campaign is conducted in order to record data to create HR-ENCs. Using this data, initial features for the HR-ENCs can be created and mapped to be able to use this data when navigating in the harbor area. Further, we consider potential applications as well as the overall benefits for using HR-ENCs in the context of highly automated shipping, showcasing identified challenges in the generation and application of HR-ENCs. Chapter 2 provides an overview over current approaches in various domains, followed by chapter 3 introducing HR-ENCs and describing the overall infrastructure for providing and distributing HR-ENCs. This is followed by chapter 4 for the generation of HR-ENCs and possible applications. Chapter 5 finishes off with an outlook and identified challenges for HR-ENCs.

2. CURRENT APPROACHES IN OTHER DOMAINS

2.1. Environment perception and connected vehicles

The demand for a more accurate perception and representation of the environment to increase the overall safety and availability of representative data is not exclusive to maritime navigation, as this research area is also approached in other domains. In the following, approaches in the automotive, railway and maritime domain are presented, completed by insights to applications in aviation and ground excavation. Finally, conclusions for a process model for environment perception are drawn.

A dominant field in research is vehicle localization and navigation, often approached in the automotive domain to improve the availability and safety of autonomous applications or driver assistance systems (Cai et al., 2022; Poulose et al., 2022; Sauerbeck et al., 2023; van Gaalen et al., 2020; Zhang et al., 2023). In this context, it is crucial to demonstrate that systems are safe and capable of handling a wide range of situations in a safe manner. A common approach is simultaneous localization and mapping (SLAM), by estimating the geometrical structures and features around the vehicle while positioning itself within the reconstruction, for example using vision or LiDAR perception (Debeunne and Vivet, 2020). Using a SLAM-based approach, a detailed 3D model can be created, also depending on the type of localization used, either global localization using information from GNSS and other on-board sensors, absolute localization by estimating the position and orientation of the vehicle relative to perceived map features or relative localization by, for example, estimating the location according to the vehicles starting location (Poulose et al., 2022).

A semantic 3D map is built by Zhang et al. (2023), and then matched with an already existing local map stored in a database. This way, the positions of the sensors can be estimated from the perceived information. van Gaalen et al. (2020) are relating the environment perceived from a radar-sensor to previously recorded LiDAR measurements to improve vehicle localization and to further validate if the perceived environment resembles the LiDAR ground truth. Also Sauerbeck et al.

(2023) are creating a high definition map for autonomous driving using LiDAR scanners by generating semantic maps and referencing it to the vehicle's GNSS trajectory. Further related work in ensuring vehicle localization and safe navigation is approached in Hamieh et al. (2019), targeting the construction of high definition maps of road environments through LiDAR, as well as Ilci and Toth (2020), approaching high definition maps by integrating LiDAR, GNSS and IMU sensors to support autonomous navigation.

Keeping maps up-to-date is approached by Liu et al. (2021), sharing information on the environmental perception among connected vehicles to achieve a dynamic map in real time, leading to an improved accuracy in the vehicle's localization, as well as by Kim et al. (2021) and Pannen et al. (2020), collecting data from other traffic participants and using it to reduce critical deviations in maps to provide accurate, updated road information without the use of expensive mapping systems.

Besides the automotive domain, localization and mapping techniques are used in the railway and maritime domains as well. Wang et al. (2015) are creating a digital map of a rail network to support the localization of a train itself, enabling further applications in railway driver assistance systems or vision-based maintenance. The impact of reliable knowledge for safety-critical railway signaling systems is described in Grosch and Crespillo (2020), mentioning the need for precise railway track maps, as the quality will have an impact on estimated train positions and velocities. A real-time high-precision map construction of railways to assist the localization of trains using a SLAM-based approach is proposed in Wang, Y. et al. (2022), aiming to enable the development of intelligent systems for the railway domain.

Hu et al. (2022) are sensing the environment in maritime berthing maneuvers using LiDAR to increase safety in these maneuvers, aiming to estimate the berthing state of a vessel. A solution for the perception of maritime objects, classification and tracking of potentially critical targets in real time is proposed by Lin et al. (2022). The mapped environment and tracked targets deal as a basis for further autonomous maneuvering operations. Furthermore, the authors emphasize on the challenges in the maritime application, especially highlighting the impact of waves and tides, as well as farther distances as opposed to urban automotive applications. Sawada and Hirata (2023) apply the SLAM-based approach in the maritime domain, creating a LiDAR point cloud of a coast. The authors aim at providing a highly accurate map that can be used for autonomous navigation applications, targeting the problem of sensor redundancy in case that GNSS-based sensor systems can fail and impact the capability of the vessel to navigate safely.

Other fields for perceiving the environment are described in Lalak and Wierzbicki (2022), in which the safety near airports is ensured through identifying and classifying potential aviation obstacles from aerial observation, perceived by unmanned aerial vehicles, retrieving accurate data on the location and height of objects, e.g. cranes with their area of movement. The goal is to update existing databases on aviation obstacles using this mapped data. Further, Rasul et al. (2021) and Wang, J. et al. (2022) describe perceiving terrain information in ground excavation and surface mine applications to obtain accurate ground information in order to enhance the capabilities of automated excavation as well as autonomous vehicles. Since the environment in these applications is fast-changing, up-to-date information on the environment is necessary.

2.2. Process model for environment perception

When looking at the need of more accurate information on object positions to achieve a higher accuracy in navigation or to enhance autonomous operations in various domains, it is apparent that there is a common shared process in perceiving the environment and taking actions based on the derived and interpreted information from the environment described in literature. Gruyer et al. (2017) describe perception stages for sensors deployed in automotive applications, aiming at the development of Advanced Driver Assistance Systems (ADAS) that are dependent on a reliable perception of the environment. They outline a process that contains the observation of the environment, followed by processing as well as the interpretation of information. Additional steps include the prediction of future states of the road as well as the vehicle acting based on the information at hand. Zhu et al. (2017) follow a similar approach, describing a perception process that includes localization and map building, finally used in the decision making process for path planning in the automotive domain. Hartstern et al. (2020) also present a sensor data processing chain for automated vehicles, in which sensor data fusion creates an environment model that is then used for the functions of ADAS.

Our process shown in Figure 3 is derived from Zhu et al. (2017), Gruyer et al. (2017) and Hartstern et al. (2020), displaying three generalized steps. In the first step, the environment is captured to collect data on e.g. the surrounding infrastructure. This is done by using suitable sensors relevant for the field of application. Afterwards, sensor data is processed in order to gain relevant information on the environment or to transform it into a usable data format. Sensor data processing can also include the georeferencing of data, to precisely localize the perceived environment. As a final step, the processed data is interpreted to integrate it into the use case to be able to perform further steps. This can apply to steps described within the related work, e.g. updating existing databases on object positions within the environment or as a base for further advanced applications, such as automated systems or collision avoidance systems. In general, processing is dependent on the used hardware and can also be limited by it, especially when the choice of sensors results in different amounts of data that is collected.

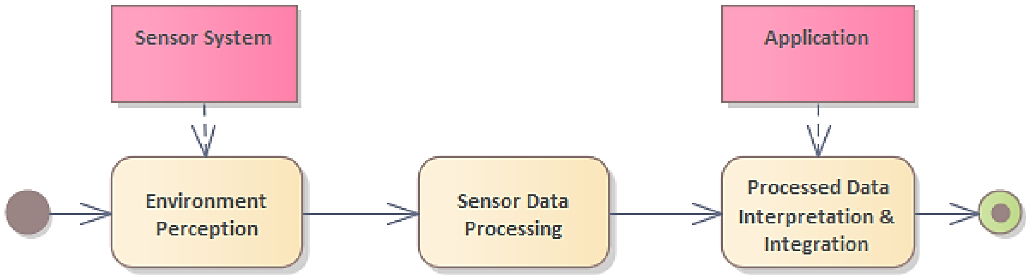

Figure 3. Generalized process model for sensors perceiving the environment and this data being used to support applications, as derived from Zhu et al. (2017), Gruyer et al. (2017) and Hartstern et al. (2020)

The following chapters are based on this process model to be able to represent challenges brought with the application in the maritime domain. Further, data sharing between vessels is considered to increase the accuracy and currentness of perceived data, extending on the concept of interconnected vehicles in the automotive domain.

3. METHOD TOWARDS HIGH-RESOLUTION ELECTRONIC NAVIGATIONAL CHARTS

3.1. High-Resolution Electronic Navigational Charts

Given the degree of complexity in automated shipping, a reliable solution is needed on how to perceive the environment in harbors to be able to enhance SA. When looking at a typical harbor infrastructure, several requirements and circumstances have to be considered: First of all, a harbor can be considered as a dynamic environment, foremost resulting from the presence of moving objects like vessels, buoys as well as its infrastructure like berths or locks with moving lock gates. To complement this, dynamic environmental conditions can also influence the safe navigation of the vessel in the harbor, especially when low visibility or strong winds reduce the maneuverability of vessels. Further, harbor traffic needs to be organized in order to better handle peak traffic times and servicing the vessel while at berth. Also, different sensor systems are already used in harbors and maritime applications, ranging from simple radar applications to data stemming from the AIS system as well as conventional communication systems that are equipped on most vessels.

For our goal to verify and amend ENCs and to introduce SA in harbor areas, we introduce a loosely-coupled sensor fusion framework for the generation of HR-ENCs. By identifying discrepancies between real-world observations and objects charted within ENCs, we aim to map current conditions within the maritime environment. However, generating up-to-date and consequently actionable HR-ENCs requires local assessments of the respective harbor areas. For this reason, our framework is based on a synergy of complex components: in-situ environment observation, object identification and localization, as well as a comparison with the corresponding navigational charts.

Following this approach, we aim at continuously updating and checking the accuracy of ENCs with the goal to detect deviations or to identify new hazards, and to maintain their reliability and effectiveness over time. With this, a continuously updated map of the harbor is available in form of an HR-ENC, that displays the accurate and current harbor environment. The resulting HR-ENCs can then be distributed between vessels and infrastructure, to increase SA for various vessels navigating in the harbor area.

3.2. Feasible technology for environment perception

While ENCs provide a versatile basis for navigation, their potential for outdated or incomplete information poses inherent risks, particularly in narrow or crowded harbors. To sample the ship's surroundings and capture geometric information on the maritime environment, a targeted selection of sensors is required. These sensors will act as critical interface between regulatory and the in-situ situational awareness, facilitating near real-time environmental detections for safe autonomous operation. Robust and reliable detections are enabled by using complementary and redundant sensor setups.

We propose an architecture based on a loose coupling between individual perception systems and charting frameworks. This allows for a flexible adaption to different environments, vessel types and regulatory requirements without rigid synchronization across all sensing modalities. By not mandating a single static update frequency, different sensor modalities can be easily combined and the setup can be extended further for increased safety. Building on findings by Pieper and Hahn (2024) and practical trials, it becomes apparent that the strategic fusion of 3D-LiDAR, Radar, GNSS and IMU systems offers a robust pathway to high-fidelity environmental modeling, which balances resolution, coverage and operational resilience.

For the purpose of this paper, camera-based techniques are used as well, although not used for the geometric sampling of the environment but to detect object classes of maritime objects that are then referenced to the data of the 3D-LiDAR. We believe that the focus in safety-critical applications lies on reliability in unpredictable or previously unknown situations, which is increased by geometric sampling methods.

LiDAR systems use targeted laser beams to produce dense, high-resolution 3D point clouds. These point clouds form the basis of detailed object mapping, distance estimation and classification. As demonstrated in Sawada and Hirata (2023), LiDAR is able to capture entire scenes with great spatial detail, which is necessary to differentiate critical harbor structures, such as quay walls, buoys and mooring facilities. However, it is susceptible to adverse weather conditions, requiring complementary sensor modalities for robust detections. To augment LiDAR, a high-resolution radar system is used to maintain detection reliability under conditions such as fog, rain or wave undulation (Zang et al. (2019)). Radar has high dependence on an object's radar cross section, resulting in weak signals from less-reflective objects, such as wooden or small structures. Still, it presents a robust tool for long-range detections and complements the system by ensuring that critical objects are not missed in poor visibility. Effectively, we propose to use LiDAR for detailed close-range mapping in benign conditions, while radar is used for robust distance estimation and obstacle detection under adverse weather or in situations of visual obstruction.

Positioning and orientation information remains an essential part to generate precise HR-ENCs. We propose the use of Differential Global Positioning Systems (DGPS) to provide high-accuracy positional estimates that are critical to align sensor-derived object positions with the global coordinate frameworks. This step is necessary for coherent integration of locally recorded LiDAR and radar detections with global HR-ENC. Meanwhile, Inertial Measurement Units (IMUs) capture vessel dynamics, that are used to correct for vessel pitch, roll, and yaw, which would otherwise distort point cloud alignment and object localization.

For the generation of HR-ENCs, we use harbor-side sensors as well as sensors mounted on the vessel itself. Since there is no guarantee that port-side sensor data is available in other locations or that this data can be accessed for the construction of HR-ENCs, the vessel-side sensor data is our primary source of information. Each vessel that is equipped with sensors collects data as it maneuvers through the harbor.

Generally, the positioning of the sensors should deliver the greatest respective benefit for navigation. Specifically, vessel-mounted sensors capture dynamic obstacles along operational routes, while port-side installations offer persistent, stationary observation of critical areas such as locks, piers and narrow passage ways. For vessel setups, bow-mounted LiDARs and radars combined with inertial measurements enable stable mapping during maneuvers, while quay-side sensors benefit from elevated and unobstructed placements to maximize coverage.

This sensor setup builds an initial foundation for HR-ENC generation. However, we acknowledge that the performance of spatial perception can be influenced by hardware limitations and environmental factors. For this reason, the impact of, for example, range constraints, susceptibility to weather or water reflections and moving pontoons, has to be considered in advance. The current integration process is designed to account for uncertainties, yet ensuring that HR-ENC updates remain both accurate and reliable over time may require more sophisticated sensor suites.

3.3. Infrastructure for providing and distributing High-Resolution Electronic Navigational Charts

A reliable and robust data-sharing infrastructure is essential to enable precise navigation, support remote operators and provide a basis for the development of autonomous navigation systems. Such an infrastructure aligns conceptually with ongoing standardization efforts like the IHO S-100 series and can contribute to future extensions of S-101-based ENCs by integrating dynamic environmental data. While generating HR-ENCs already poses a challenge, achieving the next step of using HR-ENCs by sharing these charts can gain significant synergy effects. These effects take place when data about the perceived environment is shared either among vessels, with relevant on-shore actors like ROCs or harbor operators, as well as official regulatory agencies. This data sharing involves distributing the HR-ENCs between several stakeholders. By sourcing data for HR-ENCs from multiple vessels, HR-ENCs are allowed to be compared and validated across different vessels, times and environmental conditions. This comparison and validation process will help to improve these charts and to provide an increasing SA. As a result, even vessels without their own sensor installations can navigate more effectively by taking advantage of the HR-ENCs sourced and updated by other vessels. This necessitates a robust system for managing the data and generating HR-ENCs.

Figure 4 presents a simplified representation of a harbor area, showing two vessels with distinct sensor setups for environment perception as well as typical harbor features such as a crane, a floating pontoon, piles, a bridge, buoys and a lock, which marks the harbor's entry. These features are critical for navigation and must be accurately charted in the HR-ENCs, as they pose navigational challenges for both autonomous and remotely operated vessels. The depicted scenario includes a Data Station, as well as a ROC. Every component involved in the process of distributing HR-ENCs or remote operation plays an important role in the overall infrastructure:

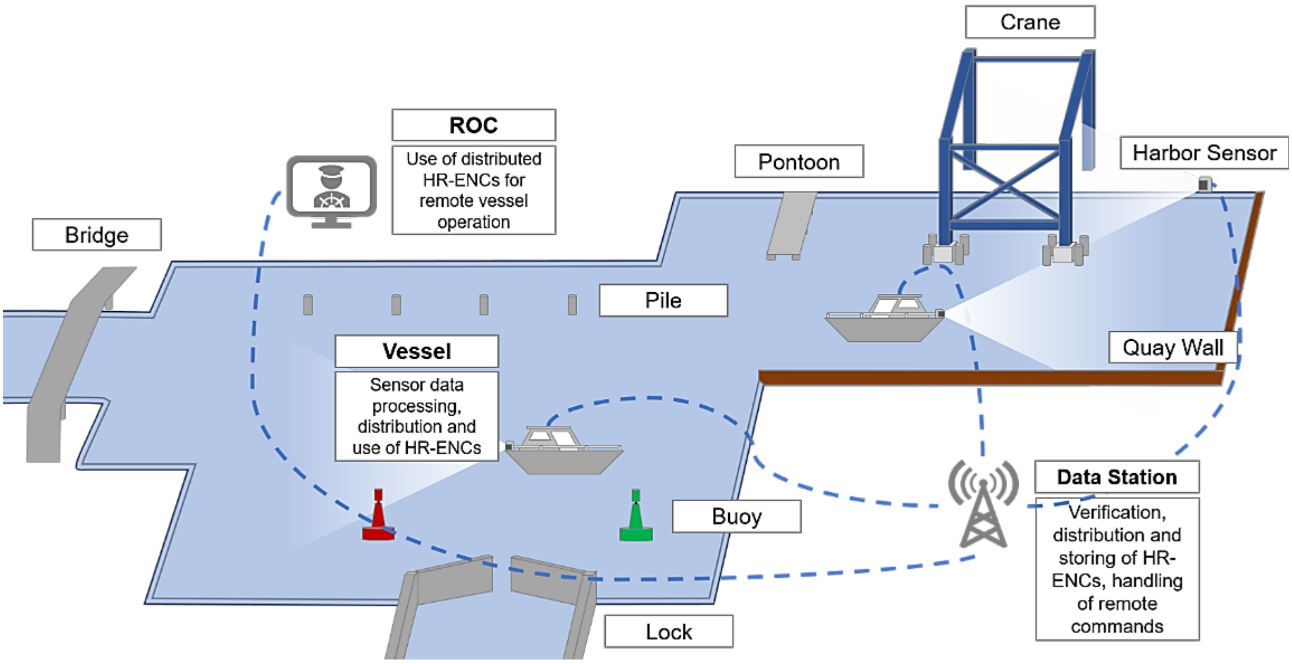

Figure 3. Infrastructure and needed components to distribute HR-ENCs between vessels, Data Station and Remote Operation Center in a simplified harbor environment including relevant S-101-Features

<u>Vessel</u>: In this context, we differentiate between two types of vessels. One vessel type is equipped with sensor equipment needed to generate HR-ENCs (perceiving vessel), while the other vessel type is without such equipment (receiving vessel). While the former collects environmental data and is able to generate HR-ENCs as well as to provide sensor data to the Data Station to generate HR-ENCs on the Data Station, the latter benefits from accessing these charts through the Data Station. This setup enhances navigation for all vessels entering the harbor, providing them with timely HR-ENCs.

<u>Data Station</u>: The Data Station is used as a middleware to retrieve data collected by vessels with sensor equipment. It is also meant to relay communication from the ROC to vessels and vice versa, effectively realizing a vessel-to-vessel and vessel-to-infrastructure communication. In the harbor use case, the Data Station holds and verifies a HR-ENC generated with sensor data received by vessels, which is consistently updated by vessels perceiving the harbor environment and sending new data to the Data Station. The integrity of the data is checked by the Data Station to verify the legitimacy and trustworthiness of received data, ensuring that only validated and recent information contributes to the HR-ENC, effectively fusing data from all vessels in the area. Further, the Data Station receives data from the harbor-based sensors installed along the quays, integrating these measurements for further accuracy improvements. By integrating multiple data sources, one central HR-ENC is maintained by the Data Station, which can be provided to vessels entering the harbor area and to ROCs. If a vessel is not equipped with any sensors, it can still benefit from the data provided by the Data Station. Extending on the Jarßum Harbor use case, the Data Station can be used as a central station for several regions of interest, therefore covering all communication and data handling in a centralized manner.

<u>Remote Operation Center</u>: The ROC benefits from consolidated, high-resolution situational data, reducing operator workload and enhancing decision-making in complex harbor environments. In particular, the operators are benefitting from the increased SA through the availability of each vessel's sensor information, further being integrated into the central HR-ENC provided by the Data Station. The central distributed HR-ENCs are then used for remote operation, allowing for more precise navigation. In remote operation, the ROC sends remote commands to vessels via the Data Station.

3.4. Generating High-Resolution Electronic Navigational Charts

To systematically generate HR-ENCs leveraging multiple sensors, we propose a sensor fusion approach as depicted in the activity diagram in Figure 5. Specifically, in accordance to chapter 3.2, we employ a loosely-coupled, object-level sensor fusion, combining high-resolution camera data for object identification based on a maritime dataset. LiDAR point clouds are utilized to achieve spatial consistency and depth resolution. By this, the LiDAR point clouds are segmented into coherent clusters. As described, radar is used as an additional supporting layer.

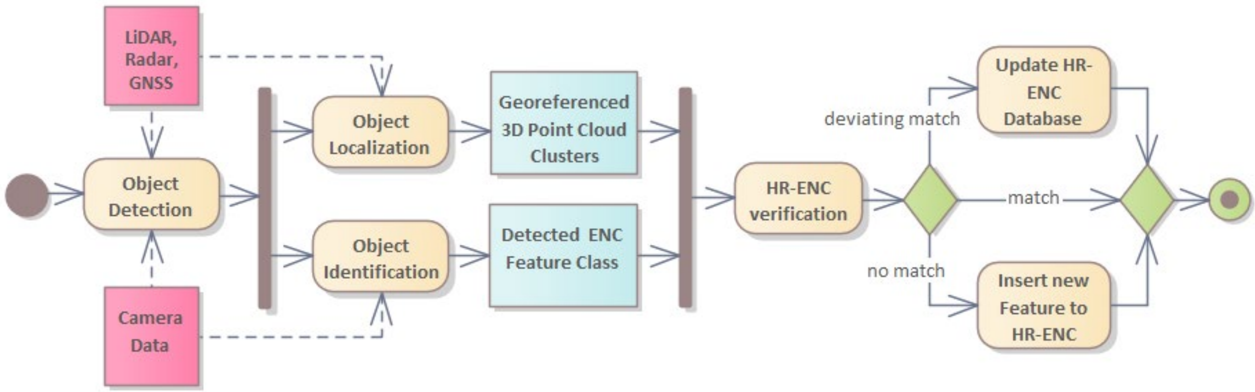

Figure 4. UML Activity diagram to generate HR-ENCs for the maritime domain based on multiple sensor modalities. After object detection, each object is assigned to a S-101 class and georeferenced. Observed objects are then compared to ENC data and discrepancies amended to the database of the HR-ENCs.

After the segmentation of the LiDAR point cloud into clusters, each cluster is classified according to the S-101 (as successor of S-57) Feature Catalogue (International Hydrographic Organization, 2024), which encode object classes for ENC creation. Similar to the scenario in Figure 4, we narrow our focus to a selected number of critical object classes resulting in a relaxed classification problem with a reduced number of categories. Nonetheless, linking the observed information to an object class is an ambiguous task resulting from the abstract nature of the point cloud. For the processing of camera data, artificial neural networks are a well-established approach to extract meaningful characteristics or features from data that are concealed from human understanding (Haghbayan et al., 2018). For this reason, we propose to use the Visible Maritime Image Dataset (Zhao et al., 2020) to train a classifier able to assign each object to a standard class. Maritime object classifications through the use neural networks are already used within the maritime domain, such as in Nita and Vandewal (2020), Shao et al. (2022) and Yoneyama and Dake (2022).

Simultaneously, we pinpoint the location of each cluster within a global reference frame using GNSS data for georeferencing (Hamieh et al., 2019), similar to automotive navigation (Ilci and Toth, 2020; Sauerbeck et al., 2023). Precise object localization is crucial for HR-ENCs, as ensuring the reliable localization of detected objects is required for actionable chart creation. The same principle is applied for the radar measurements.

For this reason, objects can be used for verification of the ENCs. Therefore, the detected objects are compared with objects extracted from an official ENC database based on class, position and shape. In case the observed object matches a feature from the ENCs within predefined tolerances, the present ENCs are considered accurate and the HR-ENCs are not updated. In case an object in the ENCs severely deviates in position or shape compared to a detected object, we update the related feature in the HR-ENC accordingly. If no corresponding feature is found, the HR-ENC is amended with the observed object. To mitigate false detections, we incorporate a temporal consistency check. This process discards momentarily observed objects while retaining objects observed consistently over time. For movable objects that can consistently change their position, e.g. buoys within certain tolerances, we propose to further collect data on recent movements that can be used as a heatmap to gain further insights on ranges of movements of these features.

This approach allows continuously updating the generated HR-ENCs while checking the accuracy of ENCs, aiming to detect deviations or to identify new hazards, and to maintain their reliability and effectiveness over time. Further, we ensure the integration of other sensor equipment in the future. By generating HR-ENCs, it will be possible to distribute these charts to other vessels for an increased SA.

4. APPLICATIONS

4.1. Use case of the Jarßum Harbor

To generate HR-ENCs in the field, a measuring campaign was conducted for the described use case within the Jarßum Harbor focusing on perceiving the environment above the water surface, extracting harbor objects and displaying the environment within the HR-ENC. For the initial measuring campaign to generate HR-ENCs, recording LiDAR and geospatial data was focused, with radar not being used initially. In this measuring campaign, no object detection was implemented, although we propose the use of solutions as already referenced in chapter 2.1 and chapter 3.4.

Figure 6. The test carrier Sally used during the measuring campaign in the Jarßum Harbor

The research vessel Sally, as seen in Figure 6, was used as a test carrier providing the necessary foundation used for capturing and georeferencing the perceived sensor data. As described by Piotrowski et al. (2025), the vessel Sally utilizes the Open Testbed Vessel architecture developed as part of the eMaritime Integrated Reference Platform (eMIR). By decoding and publishing sensor data in a standardized message format to a RabbitMQ message broker, this setup provides access to the vessels communication systems as well as sensors which are needed for generating HR-ENCs. For filtering and segmenting the perceived environmental information, the processing pipeline conceptualized by Pieper and Hahn (2024) was utilized. First, the LiDAR data was captured with a Velodyne Ultra Puck 3D-LiDAR for predefined routes and filtered by removing points within a given bounding box of the boat. This ensures that components of the vessel that are detected by the sensors, such as the cabin, are removed from the resulting point cloud. Afterwards, the water plane and noise were removed using the RANSAC algorithm and using statistical outlier removal respectively. The georeferenced position of the vessel was captured using a Saab R5 Differential GNSS-Receiver (DGPS) and heading received from the test carrier. This allowed the distance between DGPS receiver position and surrounding measurements to be calculated using the vessels position and the fixed position of the LiDAR in relation to the test carrier, which was retrieved beforehand using precise real-time kinematic (RTK) GPS measurements. The resulting filtered point cloud can be seen in Figure 7 colored by the estimated distance between the vessel's sensor positions and the measured points.

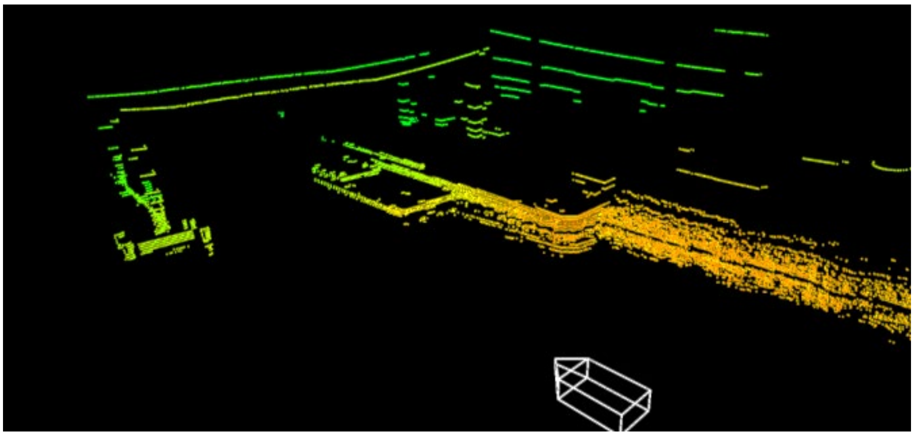

Figure 7. Resulting point cloud after filtering the LiDAR data colored by the estimated distance from vessel to the measured point. The top left shows the structure of the crane, while the vessel Sally is stylized in the bottom right as a wireframe

4.1.1. Jarßum Harbor results

After the LiDAR data has been filtered, shapes can be determined for coherent LiDAR measurements. Using several measurements from different timestamps, a solid data foundation with closed shapes is available. This data is then segmented to identify single objects in the point cloud.

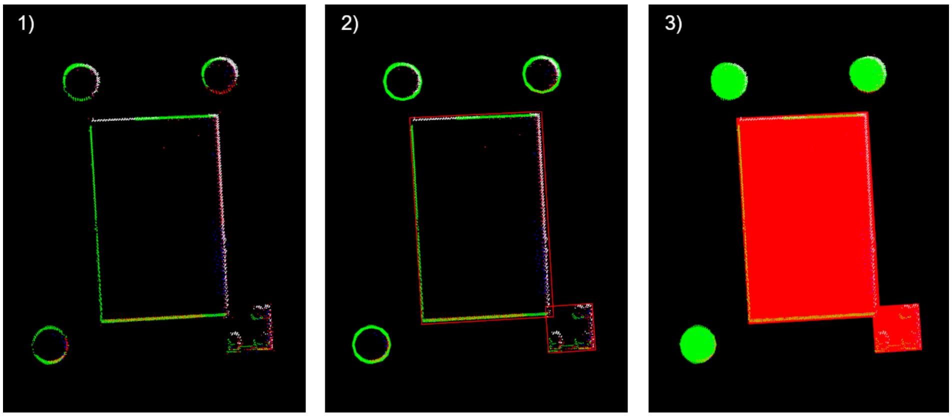

Figure 5. The combined LiDAR point cloud (1) from multiple measurements. Multiple geometries are detected (2) in this point cloud, such as two rectangular shapes and three round geometries, representing the crane pillars. These geometries are visually highlighted (3), showing the detected shapes.

Since the crane in the Jarßum Harbor consists of two base foundations, 10 structures are detected, 5 for each side. Figure 8 is showing one of the bases of the crane with 5 detected structures, estimated as circles and rectangles.

The georeferenced positioning of the segmented objects in the global coordinate system is achieved by using a coordinate transformation that converts the local coordinates of the sensors on the ship into global coordinates. This transformation is based on a precise calibration of the relative positions of the DGPS receiver and LiDAR sensor. Real-time kinematic (RTK) GPS is used to calculate the relation of object positions relative to the DGPS receiver. To position the objects a map, a transformation from UTM (Universal Transverse Mercator) coordinates is required, which indicate the global position in meters, to WGS84 (World Geodetic System 1984) coordinates, as this corresponds to the navigational chart standard. Results of this processing step are illustrated in Figure 9.

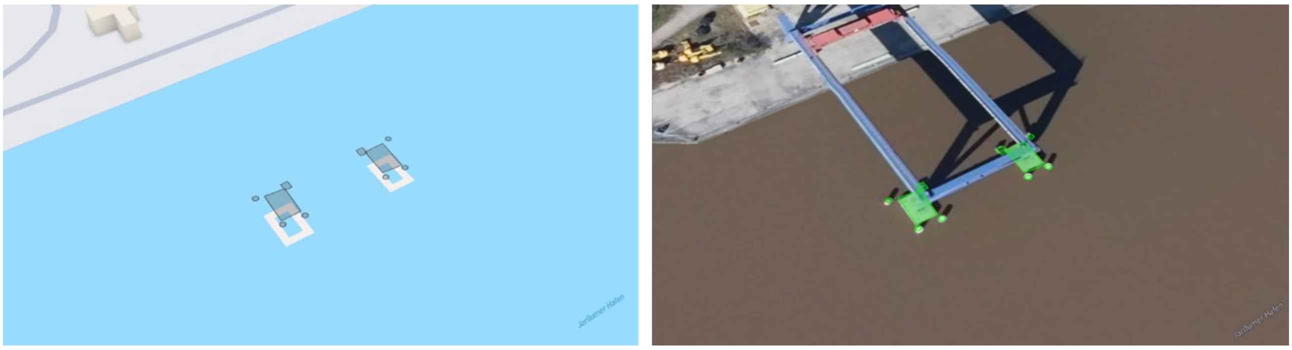

Figure 6. Georeferenced plots of the detected shapes, on a map (left) and on a satellite image (right) (Imagery ©2025 AeroWest, Airbus, CNES / Airbus, Maxar Technologies, Map data ©2025 GeoBasis-DE/BKG (©2009), Google)

Comparing the detected shapes with the ENC displayed in Figure 2, it can be seen that more objects are detected for the base of the crane than defined in the ENC. Each side of the foundation of the crane consists of five detected shapes, while the ENC only represents two each. By adding height information, the results can be displayed in 3D as an additional layer on the ENC. Figure 10 is showing the added 3D measurements for the structures of the base of the crane in the Jarßum Harbor. Data for further measurements or maritime objects can also be added to the 3D layer of the ENC.

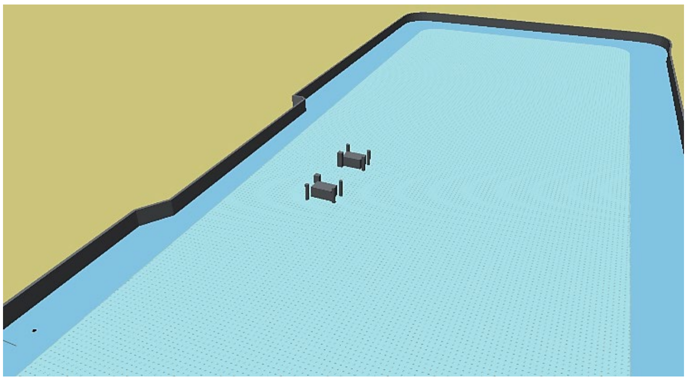

Figure 7. Showing an added 3D layer to the ENC for experimental purposes, displaying the base of the crane resulting from the LiDAR data (Underlying chart: Professional+ chart data from Lloyd's Register/i4Insight in a ChartServer solution from ChartWorld.)

To analyze error propagation, we estimate the total global object detection error, E_{Global}, similar to Pieper and Hahn (2024). This error is given by the sum of the combined absolute positioning errors adjusted for the maximum error in the orientation estimation. However, the upper limit for deviation in object positioning is calculated by the absolute error in the DGPS position (±0,4m), the positional error of the LiDAR position relative to the DGPS (±0,1m) and the maximum error in object localization based on the LiDAR returns (±0,1m). Additionally, the worst-case angular deviation (±1,0°) compounds over the distance from DGPS to the object center (e.g. 50m), yielding the maximum detection error of

$$|E_{Global}| = |E_{DGPS}| + |E_L| + |E_{LR}| + \tan(\alpha_{dev}) * d < 1{,}5\ m. \quad [1]$$

However, this estimation is only based on a single frame and thus far worse than the error for the reconstructed model over multiple frames. This is corroborated by previous field tests, which gave error results consistently below 0,6m, falling within the operational tolerances for harbor structures based on the optimal resolution defined in sections 4.8.1 and 6.4 of the S-101 specification (International Hydrographic Organization, 2024). In general, these results show the viability of adding information of 3D measurements to a map, as the data can display geometric shapes of the observed objects. Having this data available can open up possibilities to increase accuracy in navigation and in the further use of HR-ENCs. Further applications as well as challenges are discussed in the following chapters.

4.2. Further fields of application

Using HR-ENCs generated by in-situ condition assessment opens up many possibilities for applications in the maritime domain and might serve as a key enabler for highly automated shipping. On the one hand, HR-ENCs enable the verification of existing ENCs, improving the accuracy and reliability of the most fundamental navigation data by functioning as a ground truth. On the other hand, they provide mariners assistance through a detailed and up-to-date view of their surrounding marine environment, becoming the basis for both manual and automated route planning and improving SA. This is a crucial enabler for autonomous and remotely operated vessels, where no human is on-board to act as a fail-safe, and wrongly depicted or missing objects entail critical risks of collision when relying on this information. HR-ENCs will therefore increase safety and efficiency in autonomous and remote vessel operations. Further, this combats the shortage of skilled labor in the maritime domain (BIMCO and International Chamber of Shipping, 2021) and allows for a reduction of costs in vessel operations in the long run. By using more accurate data for navigation, multiple vessels can be operated by fewer remote operators, maintaining a manageable workload. Similar challenges are also faced in the automotive (Hamieh et al., 2019; van Gaalen et al., 2020) or railway domain (Grosch and Crespillo, 2020; Wang et al., 2015; Wang, Y. et al., 2022) as already shown in the chapter for related work, aiming to increase the reliability and accuracy of navigational data to improve autonomous operations. Also, when taking a look at harbor operators, being able to provide harbor-wide HR-ENCs allows to maintain a competitive advantage compared to other harbor operators. A possible application for harbor operators is to equip vessels with sensors that are consistently moving around in the harbor, such as dredging vessels.

Even beyond the foundational use for verifying officially released ENCs, HR-ENCs provide a dependable information basis for the development of advanced driver assistance systems (ADAS), e.g. collision avoidance or berthing assistance systems as in (Hu et al., 2022; Lin et al., 2022) although deviating in the underlying approach. These systems heavily depend on the accuracy and comprehensiveness of the data input, which is exemplified when considering that the condition assessment is limited to the area around the surveying vessel. The assessment of objects and their respective positions enables the constant improvement as well as the ongoing refinement of navigational systems, effectively implementing a feedback loop.

Optimally, this limitation can be countered by Multi-Ship-Operations, allowing multiple vessels to share sensor data leading to reliable HR-ENCs as we described in the HR-ENC distribution and data sharing infrastructure in chapter 3.3. Vessel-to-vessel or vessel-to-infrastructure communication can drastically enhance the performance of our approach by ensuring that crucial areas are consistently surveyed allowing all maritime participants to perform more efficient routing. Similar approaches have been considered in the automotive domain in (Kim et al., 2021; Liu et al., 2021; Pannen et al., 2020), as shown in the chapter for related work, demonstrating how collaborative vehicles can provide more accurate maps and updated road information through sharing each vehicle's perception of the environment. This process will benefit vessels without sensor equipment as well, as these vessels can rely on charts sourced by third-party equipment.

Having up-to-date information available on the environment of a harbor also offers shipping companies more reliable information on the harbor's conditions. This will help to improve planning for shipping and other operations. Further possible is the fleet-wide equipment to generate HR-ENCs, which could be distributed companywide without sharing data to third-parties, therefore realizing further competitive advantages.

The dynamic nature of maritime environments requires continuous monitoring of the harbor environment to allow for up-to-date HR-ENCs. By continuously safeguarding the integrity of maritime navigation more complex maritime challenges can be tackled, equipping vessels for interconnected future of autonomous maritime operations.

5. OUTLOOK & CHALLENGES FOR INTRODUCING RELIABLE HR-ENCS

Until HR-ENCs will be in use, several difficulties have to be addressed, ranging from regulatory to technological challenges. As reliable navigation is crucial in highly automated shipping, these challenges influence the degree of feasibility of applying HR-ENCs as well as its accuracy.

5.1. Regulatory challenges

For the regulatory challenges, one main legal challenge is data protection and data security. Encompassing various sensors and camera images, it needs to be addressed on how harbor areas can be perceived by cameras installed on vessels, especially if other vessels or people on vessels are perceived by these sensors and are therefore visible, leading to partially sensitive data being recorded. It is also important to tackle how this data is stored on Data Stations and how the access to this data will be managed and regulated. An additional legal challenge is that navigation, according to the SOLAS, should only be conducted by using official navigational charts that were issued by e.g. hydrographic authorities (*International Convention for the safety of life at sea.* International Maritime Organization, 1974). This effectively hinders the sole usage of HR-ENCs while navigating as well as the distribution of HR-ENCs for navigation purposes. Therefore, it needs to be considered in what way this can be made possible, e. g. by working closely with the responsible hydrographic authorities to enable further work with ENCs. Since sharing HR-ENCs is crucial for our approach on safe maritime navigation, this is a problem that needs to be addressed. Nonetheless, simple HR-ENCs can still be generated by using sensors equipped on vessels without amending existing ENCs or using data stemming from these charts, although the official use of this data for navigation purposes is to question.

5.2. Technological challenges

Taking a look at the future of HR-ENC distribution and on-vessel perception of the surrounding environment, it needs to be considered how the sensor and data processing setup can be made accessible for most vessels. Synergy effects for distributed HR-ENCs depend on the number of vessels equipped for generating HR-ENCs, as more data of the surrounding environment in a harbor can be captured if more vessels are equipped with sensors. By using a standardized setup on vessels, new technology will be more accessible for vessel operators as costs can be lowered. This is also necessary because of the requirements for processing various sensors and camera images on the vessels and to distribute and receive generated HR-ENCs. When navigating in narrow harbors, the communication infrastructure for receiving harbor-wide HR-ENCs needs to be reliable to support precise navigation.

Further, this also questions the quality of the measurements. In our field tests, a DGPS-based solution was used in order to reference the detected objects to a precise position. Future work needs to focus on evaluating different methods in this context, while considering the cost of equipment. Using real-time kinematic (RTK) GPS enables centimeter-level accuracy, and other literature have already explored its use for accurate navigation applications and low-cost solutions in maritime contexts (Alissa et al., 2021; Janos et al., 2022; Matias et al., 2015). Other positioning methods, such as EGNOS, which is a European satellite-based augmentation system (SBAS), are also considered for navigation applications in the maritime domain. Literature shows that EGNOS is able to outperform DGPS-based methods (Innac et al., 2022), although Specht et al. (2019) note that the accuracy of DGPS was higher than the accuracy of EGNOS when entering harbor environments in their study. It is also important to consider the availability of correctional measurements for these positioning techniques (Felski and Nowak, 2015), even if the availability in restricted waters and coastal regions is more likely as opposed to open waters. When considering the availability of GNSS data, covering possible outages is of interest as well, especially if the vessel is moving narrow harbor areas and the GNSS signal drops out for a short time period. For this, approaches such as dead reckoning or Kalman filter exist, aiming to estimate the position of the vessel while no GNSS signal is available (Kim et al., 2014; Skulstad et al., 2019).

Challenging as well is to reliably perceive obstructed objects or the backside of objects with uncommon shapes. While estimating object shapes for common objects can be achieved rather simply, complex object structures require more thorough methods. A feasible approach is to use existing data from other directions and perspectives from previously generated HR-ENCs, so that data for these structures is available. Further, applying approaches for shape fitting can aid in detecting the full shape of obstructed objects, helping in estimating the total size of the object.

For the classification of detected objects into S-101 object classes, the feature detection proposes a challenge as well. Considering a representation of all S-101 classes, a usable dataset and model for the feature detection and object classification is required. Regarding S-101 categories, not all categories can be determined by using the data as proposed by our approach on generating HR-ENCs. For the example of the Jarßum Harbor, this includes categories such as the lifting capacity of a crane or condition, radius, status and the nature of construction (materials) for further S-101 classes. Therefore, it is important to consider how this information can be derived from the data at hand, or if a manual annotation is still needed.

Further, our current approach does not cover perceiving the surrounding below the water level as this introduces different requirements and further sensor modalities in the perception of the harbor environment. As ENCs also contain bathymetric information in varying levels of detail, this is a problem that needs to be addressed as well to provide always up-to-date information about underwater obstacles and therefore realize full SA. However, equipment for measuring bathymetric information is already in use today, mostly focusing on Singlebeam and Multibeam Echosounders (SBES and MBES), with MBES offering higher detail and depth perception (Khomsin et al., 2021). In recent years, the development of bathymetric LiDAR technology has enabled to capture more detailed and complex underwater structures in shallow water compared to traditional MBES systems (Awadallah et al., 2023; Li et al., 2022). Combining the advantages of both systems, multiple approaches to generate point clouds and reconstruct underwater object shapes by fusing bathymetric LiDAR and MBES data have been proposed (Kulawiak and Lubniewski, 2016; Li et al., 2022). Thereby these techniques allow to capture detailed bathymetric information, that can be incorporated into HR-ENCs. However, as our current approach focuses on perceiving the harbor infrastructure, bathymetric information will be addressed in future work to enhance HR-ENCs.

6. CONCLUSION

Providing a reliable foundation for the operation of highly automated systems and increasing overall safety of maritime navigation is a common research area, as shown by many related works. We focus on safeguarding the integrity of ENCs by proposing an approach for generating up-to-date HR-ENCs for the maritime domain, which incorporates data from local harbor condition assessment. We discuss fitting sensor techniques for environment perception and offer a view on infrastructure for distributing and using HR-ENCs, gaining synergy effects in remote operation scenarios with multiple vessels. Results from the use case in the Jarßum Harbor show the potential for generating HR-ENCs in the field, providing insights into how the LiDAR data can be used for detecting objects and shapes in the harbor. Further, we discuss potential applications of the HR-ENCs, offering a broad view on the topic with a focus on highly automated maritime systems and benefits for maritime navigation. Also, current challenges in the future use of HR-ENCs and connected challenges in the maritime domain are discussed. Future work will continue to explore further collaborative data-sharing mechanisms between multiple stakeholders to expand the coverage and usability of the HR-ENCs as well as methods to generate precise harbor-wide HR-ENCs, enabling safe maritime operations.

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CONFLICT OF INTEREST

The authors declare that there are no conflicts of interest.

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