Enhancing Situation Awareness in Highly Automated Shipping using High-Resolution Electronic Navigational Charts

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***Abstract*—Highly automated vessel operations depend on accurate and reliable information about the vessel's surroundings. This paper addresses the challenges of ensuring navigational safety, even when the integrity of Electronic Navigational Charts (ENC) is compromised. In maritime navigation, it is crucial to assess where the vessel is positioned in relation to objects of the harbor infrastructure. We propose High-Resolution Electronic Navigational Charts (HR-ENCs) as a tool to capture sensor data, combining multiple remote-sensing technologies using a loosely-coupled sensor fusion framework. By accurately identifying and georeferencing maritime objects, we aim to enhance Situation Awareness (SA) and ensure safe navigation of both manned and unmanned vessels. Integrating data from camera, LiDAR and GNSS, as well as existing ENCs, we create HR-ENCs to reflect current conditions within harbors. By focusing on the detection of discrepancies between observed conditions and charted objects, HR-ENCs pose actionable harbor charts containing the relevant navigational data. Further, we outline the infrastructure to distribute HR-ENCs among maritime systems, showcasing the potential for harbor-wide, consistently updated HR-ENCs that are available to all stakeholders. In addition, we explore applications and challenges in using HR-ENCs beyond ENC verification, highlighting their potential for the development of Advanced Driver Assistance Systems (ADAS) for collision avoidance and berthing. 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.**

***Index terms*—remote operation, automated shipping, mapping, maritime navigation, Electronic Navigational Charts.**

I. INTRODUCTION

When looking at the current developments in academia and industry, Maritime Remote Operation seems to be a promising solution for the shortage of skilled labor in the maritime industry. 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 [1]) with regards to collision avoidance becomes a crucial task for remote operators [2]. 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 operation 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 such objects [3]. In addition, commonly used Electronic Navigational Charts (ENC) also contain information about the type and location of objects [4], 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 Fig. 1 to the ENC in Fig. 2.

Fig. 1. Jarßum Harbor in Emden, Satellite Image (Imagery ©2024 AeroWest, Airbus, CNES / Airbus, Maxar Technologies, Map data ©2024 GeoBasis-DE/BKG (©2009), Google)

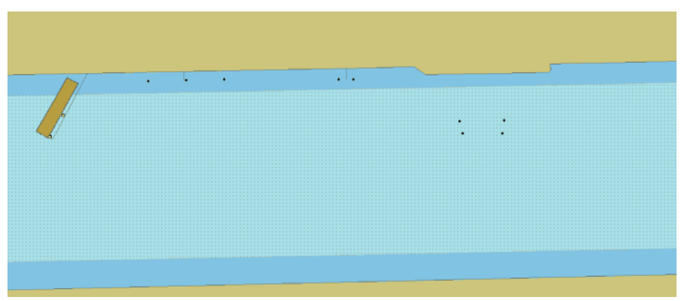

Fig. 2. ENC for Jarßum Harbor (Professional+ chart data from Lloyd's Register/i4Insight in a ChartServer solution from ChartWorld.)

The depicted crane (blue structure on the right side in Fig. 1) is not fully captured in the ENC (Fig. 2). When compared 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. A movable pontoon is visible as well (structure on the left side), and while the position on the

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satellite image appears to be the same as in the ENC, this is not always the case. Overall, features are not represented thoroughly and moving features are not considered at all, therefore questioning the accuracy of the ENCs. This describes a limiting factor for future maritime navigation, when further developed and advanced autonomous systems will be in use.

This challenge is addressed 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 work, we discuss our approach for creating HR-ENCs and lay out a communication infrastructure for the use of distributed HR-ENCs, sharing data between vessels and showcasing a scenario based on remote operated vessels. 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 II introduces HR-ENCs, followed by chapter III describing the overall infrastructure for providing and distributing HR-ENCs and chapter IV for the generation of HR-ENCs. Possible applications are described in chapter V, finishing off with identified challenges for HR-ENCs in chapter VI.

II. High-Resolution Electronic Navigational Charts

For our goal to verify and amend ENCs, 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.

To sample the maritime environment, we use locally installed sensors mounted on both the harbor quay as well as vessel-based sensors, as vessels will maneuver through the harbor and perceive the surrounding environment in various situations. Integrating complementary sensors modalities, a solid foundation for further data processing is created.

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. The resulting HR-ENCs can then be distributed between vessels and infrastructure, to increase SA for various vessels navigating in the harbor area.

III. Infrastructure For Providing and Distributing High-Resolution Electronic Navigational Charts

A robust infrastructure is essential to enable precise navigation, support remote operators and provide a basis for the development of autonomous navigation systems and collaborative data-sharing. 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 or with relevant on-shore components like ROCs. This data sharing involves distributing the HR-ENCs between several stakeholders. A broad data foundation allows data for HR-ENCs to be compared and validated across different vessels, times and

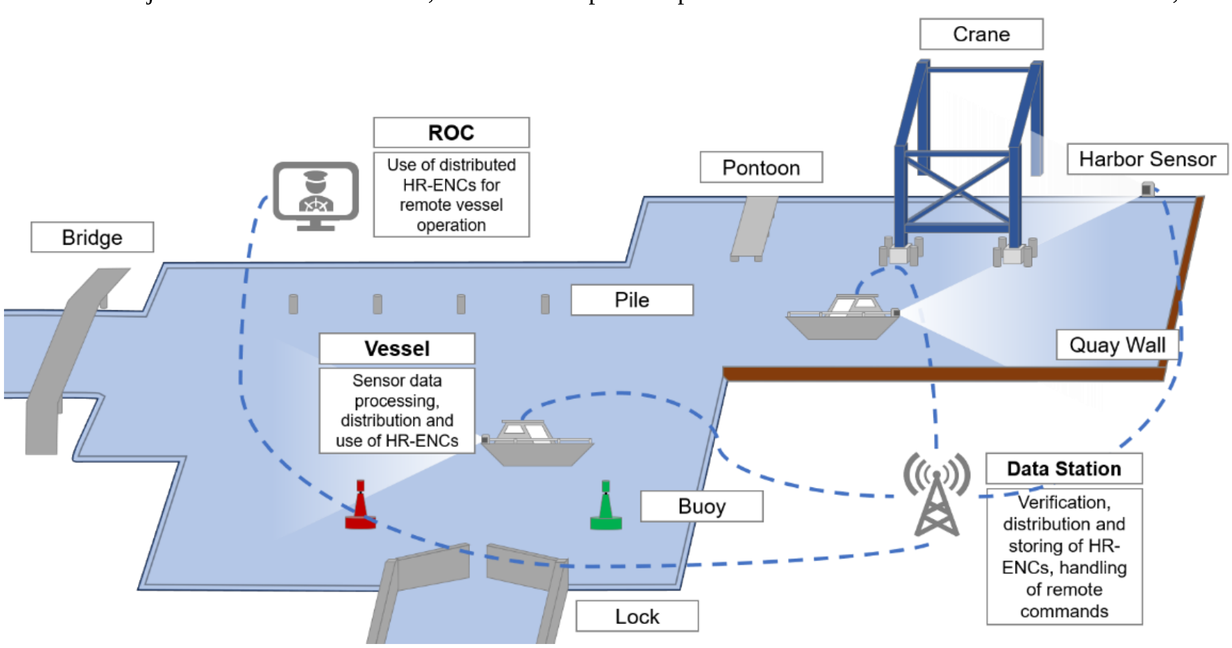

Fig. 3. Infrastructure and needed components to distribute HR-ENCs between vessels, Data Station and Remote Operation Center in a simplified harbor environment including relevant S-101-Features

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.

Fig. 3 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 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:

Vessel: 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.

Data Station: 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. This data is verified for integrity in the Data Station according to recency and accuracy of sensor measurements, 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.

Remote Operation Center: The ROC benefits from an increased SA through the availability of each vessel's sensor information 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.

IV. Generating High-Resolution Electronic Navigational Charts

To generate HR-ENCs by using different sensors, we present our approach as depicted in the activity diagram in Fig. 4. Specifically, we propose to leverage camera data for the identification of objects based on a maritime dataset due to its high spatial resolution, and complement it with LiDAR sensor data to resolve the depth ambiguity. Consequently, a loosely-coupled sensor fusion for object detection is performed, effectively fusing camera and LiDAR data to segment the point cloud into coherent clusters.

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 [5], which encode object classes for ENC creation. Similar to the scenario in Fig. 3 we narrow our focus to a selected number of critical 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 data points. For the processing of camera data, artificial neural networks are a well-established approach to extract meaningful characteristics or features from

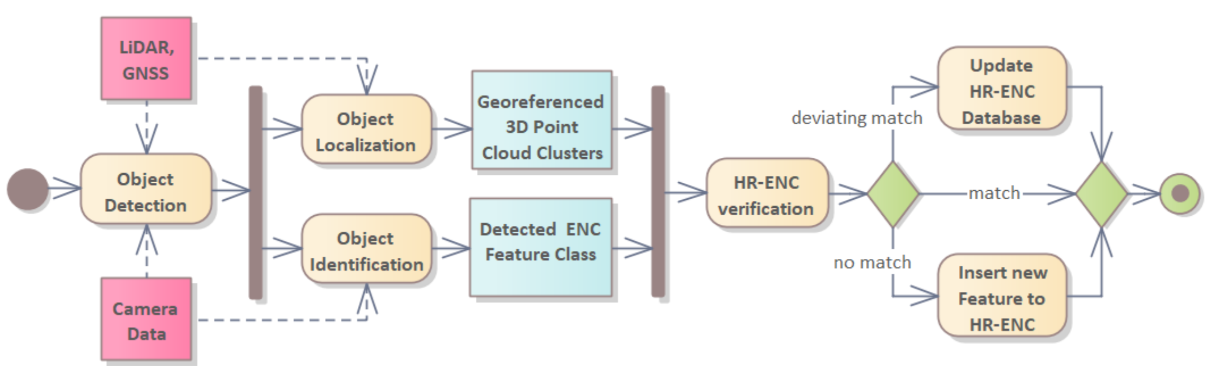

Fig. 4. UML Activity diagram to generate HR-ENCs for the maritime domain based on multiple sensor modalities. After object detection, each object is assigned to a S-101 class and georeferenced. Observed objects are then compared to ENC data and discrepancies amended to the database of the HR-ENCs.

data that are concealed from human understanding [6]. For this reason, we use the Visible Maritime Image Dataset [7] to train a classifier able to assign each object to a standard class.

Simultaneously, we pinpoint the location of each cluster within a global reference frame using GNSS data for georeferencing [8], similar to automotive navigation [9], [10]. Precise object localization is crucial for HR-ENCs, as ensuring the reliable localization of detected objects is required for actionable chart creation. Distance estimation and georeferencing increases precision and applicability by providing a global frame of reference.

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. Similar comparisons are described in [11], updating aviation obstacle databases to increase air traffic safety. 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.

V. Applications

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 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 [8], [12] or railway domain [13], [14], [15], 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 [16], [17], 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 III. 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 [18], [19], [20], 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.

VI. 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.

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 using information based on official ENCs and distributing HR-ENCs. Since current ENCs are not meant to be shared, 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.

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.

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, 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. While our current approach focuses on perceiving the harbor infrastructure, bathymetric information will be included in future work and will further enhance HR-ENCs.

VII. 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. In addition, we offer a view on infrastructure for distributing and using HR-ENCs, gaining synergy effects in remote operation scenarios with multiple vessels. 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. 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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