A Conceptual Approach to Harbor Object Detection: The Potential of 3D-LiDAR-based Sensor Fusion for High Precision ENC

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Abstract: In the advancing era of autonomous maritime navigation, the precision of Electronic Nautical Charts (ENCs) is critical. This study conceptualizes a framework to validate and rectify ENCs nearly in real-time, leveraging high-resolution 3D LiDAR, DGPS, and IMU data. The approach of this study includes a domain-specific point cloud filtering, object segmentation, classification in compliance with the S-101 standard classes and a georeferencing strategy. By comparing identified objects against ENC data, this study pinpoints discrepancies and augments the ENCs with up-to-date object information. An evaluation through field tests is proposed, complemented by Traffic Sequence Charts and reference calibration via Realtime Kinematic GPS, ensuring practical relevance of our framework to real-world conditions. The contribution of this paper lies in offering a comprehensive solution for ENC refinement, thereby facilitating safer autonomous navigation by verifying that ENCs are reflective of current environmental conditions.

Keywords: LiDAR, mapping, object detection, Electronic Nautical Charts, georeferencing, sensor fusion

1. INTRODUCTION

Electronic Nautical Charts (ENCs) serve as a long-standing tool in maritime navigation, ensuring the safe and efficient passage of vessels. However, as found by Karetnikov et al. (2017), the integrity of ENCs is frequently undermined by discrepancies between charted representations and actual conditions. These discrepancies include the misplacement or incorrect sizing of objects and the omission of crucial data, heightening the risk of vessel collisions. Confronted with narrow fairways, harbor areas, or locks, where the margin for error is exceedingly small, such inaccuracies become problematic. However, this issue gains particular significance within the context of Maritime Autonomous Surface Ships (MASS), as these vessels depend heavily on reliable ENCs for automated decision-making or berthing operations. Any inaccuracies result in an increased risk of accidents, especially when onboard sensor systems are insufficient or not available.

In practice, the criticality of reliable ENCs becomes evident in the context of high precision navigation tasks. For instance, initial experiments with a highly automated vessel conducted by the German Aerospace Center (2022) faced challenges during a high accuracy lock entry when a 2-meter discrepancy between the lock's actual position and its charted location was revealed, resulting in a near-collision.

This incident exemplifies the broader challenges in harbor navigation accuracy, necessitating systemic improvements. Illustrated by Figure 1, this issue compares the ENC of the Jarßum Harbor with a recent satellite image. Notable changes include a pontoon's lateral shift to the left compared to the ENCs. Furthermore, the representation of the loading crane is significantly oversimplified, being depicted as four pillars rather than two larger ones with each four mooring poles.

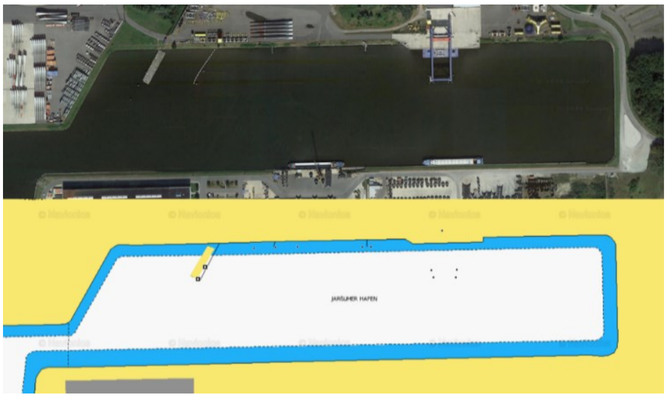

Figure 1. Comparison between the actual conditions Jarßum Harbor in Emden (top) from Google Earth, contrasting the Electronic Nautical Charts (bottom) from Navionics ChartViewer.

Continuous changes of port infrastructure demonstrate the dynamic nature of harbors and stress the necessity for ongoing review of ENCs to support the integrity of autonomous navigation systems.

This paper proposes a framework designed to enhance the reliability of ENCs by identifying and rectifying inaccuracies in the mapping of objects and shorelines. We investigate methods for detecting harbor infrastructure, realigning inaccurately mapped objects with current charts, and reporting these adjustments in compliance with maritime regulations. By addressing these critical aspects, our research seeks to provide comprehensive and actionable solutions for ENC refinement. This paper prioritizes the safety concerns of shipping companies and vessel operators. By streamlining maritime operations, it addresses the operational efficiency sought by port authorities. Lastly, the paper is dedicated to upholding the data accuracy standards required by Hydrographic Offices.

2. HIGH-PRECISION VERIFIED CHARTS

Addressing navigation challenges for MASS requires a solution that verifies harbor infrastructure detection and positioning with high accuracy, robust against various environmental conditions and integrated seamlessly with ENCs. The International Hydrographic Organization (IHO, 2021) acknowledges the necessity of adapting hydrographic standards to support autonomous maritime navigation.

Building on this foundation, ensuring the integrity of maritime navigation becomes paramount, particularly considering MASS. To achieve this, a robust method for the near real-time verification of ENC accuracy is essential. By aligning geographical and structural conditions in the harbor with the ENCs, discrepancies can be detected, revealing data inaccuracies or object omissions. The system must be capable of incorporating and synchronizing data from at least one independent source, such as in-situ sensor measurements, to provide reference information against which comparisons can be made. Here, a mechanism to detect and report identified discrepancies is crucial, fostering collaboration between chart producers, maritime authorities, and vessel operators. By facilitating collaborative contributions from maritime stakeholders, collective expertise is leveraged. This framework ensures that maintaining and updating ENCs becomes a shared responsibility, significantly enhancing navigational safety. Furthermore, adherence to international maritime safety and navigation standards has to be assured to grant regulatory compliance and uphold of all safety protocols. These requirements, listed in Table 1, are derived from the critical need to address the potential risks posed by inaccuracies in ENCs, necessitating near real-time chart validation to enhance the reliability of maritime navigation.

Table 1: Derived requirements for the proposed framework to verify ENC accuracy and report discrepancies to stakeholders.

Requirement	Description
Accuracy Verification	Able to assess and verify the accuracy of ENCs in nearly in real-time.
Deficiency Detection	Able to identify discrepancies and deficiencies in ENCs.
Data Integration	Seamless integration of data from official sources.
Stakeholder Collaboration	Framework for collaboration among maritime stakeholders.
Regulatory Compliance	Regulary conformity to international maritime standards.

3. RELATED WORK

While high accuracy ENCs are essential for the advancement of autonomous maritime navigation, Karetnikov et al. (2017) find that data inaccuracies within the ENCs might compromise their integrity. These limitations are further explored by Schmidt et al. (2018), who point out the safety risks for autonomous vessels from inadequate hazard depiction. While they propose the adoption of 2D object representations as a solution to increase the precision of charted objects at different scales, they fall short of presenting a viable implementation strategy, leaving a critical gap in practical application.

Pirillo (1999) augmented ENCs with sensor data through a computerized hydrography system for near real-time environmental data assessment, adding water quality information to the ENCs. However, this approach primarily facilitates data collection rather than addressing the verification and refinement of ENCs. Similarly, Guan et al. (2010) developed a methodology for augmenting ENC data with static data sources, such as S-57, Military Vector Chart Format (MVCF) and Computer Aided Design (CAD) data. This method aids in creating specific ENC databases for navigational safety assessments in harbors and waterways yet bypasses the essential task of in-situ data verification.

More elaborate methods rely on sensor equipment to detect objects in maritime environments. This is demonstrated by Haghbayan et al. (2018) by using a multi-sensor fusion approach for near real-time object detection and tracking. Integrating data from radar, Light Detection and Ranging (LiDAR), and cameras through a probabilistic data association method and employing a Convolutional Neural Network (CNN) for object classification, the accuracy of object localization could significantly be enhanced. Extending on these ideas, Thompson et al. (2019) utilize a 3D occupancy grid for mapping objects around an unmanned surface vehicle (USV), combining LiDAR data with a visibility horizon to map and classify objects for path planning. Significant progress has been made in detecting both dynamic and static objects. However, these methods lack a rigorous ground truth assessment and fail to cross-reference results with ENCs. Additionally, they do not provide identified objects to others.

These endeavors underscore a prevalent issue: the lack of methods to actively scan the environments for the verification and supplementation of ENC data. Despite these limitations, we recognize that this data is in high demand and for the lack of alternatives used for autonomous collision avoidance and path planning applications, displayed by Blindheim et al. (2021). Representative studies, like Delobel (2018), show that unlike the maritime sector, the automotive and robotic fields have advanced in creating and refining environmental maps. Even more, Rife et al. (2010) have demonstrated how these maps can be used for collaborative navigation strategies.

Tang et al. (2023) offer a contemporary perspective by constructing static environmental maps using 3D LiDAR, showcasing substantial performance improvements. However, stemming from the robotic domain, their work does not address the integration of data according to maritime standards. Marking a missed opportunity for ENC accuracy refinement, it highlights the need for a new approach.

4. SYSTEM DESIGN FOR OBJECT IDENTIFICATION

Verifying the accuracy of ENCs is crucial for guaranteeing the safety and efficiency of vessel operations. However, reflecting on the related works, it becomes clear that this has not been sufficiently achieved. Same is true for traditional mapping approaches, which utilize static chart data and manual surveys and acknowledge the necessity for accurate environmental information. Still, they frequently fall short in capturing fine details from marine environments. This becomes particularly clear when capturing three-dimensional objects within harbor areas, such as the crane in Figure 1, omitted from ENCs. In response to these limitations, this research proposes a conceptual approach leveraging a vessel-mounted 360-degree LiDAR scanner to enhance the utility and reliability of object identification for ENCs for autonomous maritime navigation.

4.1 System Design

As detailed by Wang et al. (2022), LiDAR scanners generate dense collections of three-dimensional data points, or point clouds, offering precise depth estimation that retains the three-dimensional data commonly lost in camera-based techniques. Notably, LiDAR surpasses radar systems in resolution, offering a more detailed and accurate depiction of maritime environments. By providing the necessary accuracy and resolution for effective object segmentation and classification, LiDAR is the preferred choice for this application.

As a consequence, we propose to employ a single 3D-LiDAR sensor strategically mounted on the bow of a vessel, allowing to scan the surrounding scene beyond a radius of 100 meters. To enhance the LiDAR's performance, the system incorporates a 6-axis 10Hz Inertial Measurement Unit (IMU) for precise orientation tracking and a Differential Global Positioning System (DGPS) receiver for accurate global positioning. This combination of sensors serves a dual purpose: while the LiDAR provides detailed spatial data about the environment, the IMU and DGPS receiver work in tandem to accurately determine the vessel's position and orientation, ensuring that detected objects can be precisely located and categorized.

This integrated sensor system is designed to detect potential navigational hazards, enabling the immediate positioning and sizing of objects around the vessel. Leveraging detailed shape information extracted from LiDAR-generated point clouds, the system can identify maritime objects, including predetermined landmarks, buoys, pontoons, and shorelines. Identified objects are then matched against the ENC data. When discrepancies arise - such as objects not aligning within a predefined perimeter of their ENC counterparts or significant variances in size - the system flags these anomalies. Each identified discrepancy is meticulously cataloged in accordance to the IHO (2018) S-101 (as successor of S-57) standard, ensuring the information is readily accessible to maritime stakeholders. This process is illustrated in Figure 2, providing a visual overview of the system's operational workflow.

4.2 Filtering

Prior to processing, we filter the LiDAR data to correct for sensor inaccuracies and environmental effects. Filtering significantly improves data quality, especially in changing maritime settings, adaptively removing erroneous data points. We employ statistical outlier removal and perform noise reduction using a bilateral filter, maintaining edge integrity, as detailed in Qi (2020). Also, we specifically target undesired measurements from the boat and water, latter being a common challenge in analyzing maritime environments.

Traditional methods, such as applying a simple height constraint, may inadvertently discard valuable data points. Based on Wang et al. (2022), we advocate for the use of Cloth Simulation Filtering (CSF), to distinguish between waves and

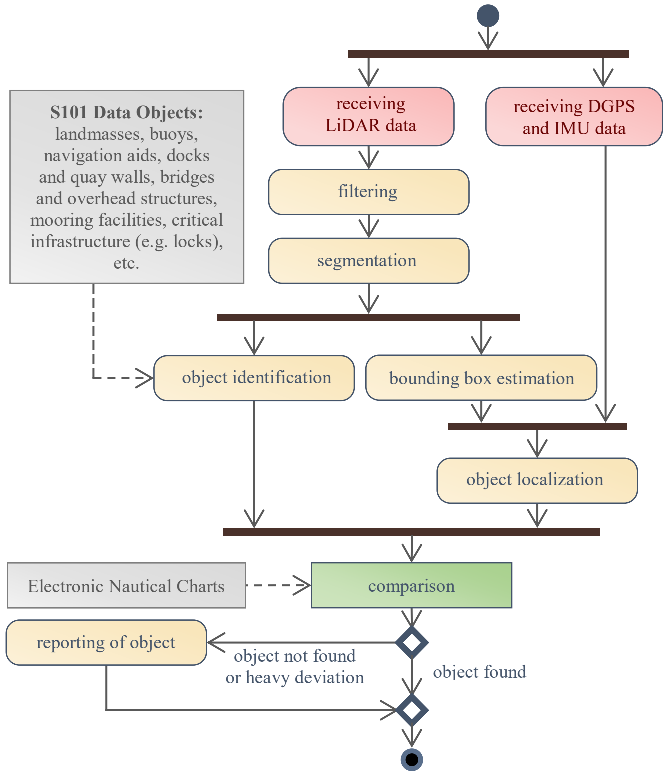

Figure 2: UML-Chart of the processing pipeline. Only LiDAR data undergo preprocessing (filtering and segmentation), dimension estimation, and object identification based on S-101 standard categories. Supplementing DGPS and IMU data, identified objects are georeferenced for comparison with charted objects. Identified objects not found or significantly deviating from the ENCs are reported via a data base in compliance with S-101 standard.

elevated structures. Wang's findings suggest CSF allows for a more nuanced analysis of harbor infrastructure by handling wave reflections, where methods like Random Sample Consensus might struggle due to the variable height of LiDAR returns. Integrating these advanced filtering techniques, our proposed approach seeks to elevate the relevance of the remaining data points. Although discarding data points might be unintuitive at first, increased data reliability is crucial for object identification.

4.3 Segmentation

After filtering the LiDAR data, the point cloud becomes more structured and can be divided into smaller, more manageable segments, each representing distinct objects or features from the scanned environment, as in Thompson (2019). This segmentation is a crucial step as it converts disordered point cloud data into an organized format that can be better analyzed and understood. The primary goal of the segmentation is to accurately identify and isolate individual objects, such as anchored ships, landmasses and aids to navigation (AtoN), within the harbor environment.

However, object segmentation is particularly challenging since objects not only vary significantly in size, shape, and reflectivity, but as a result of the inherent complexity and dynamic nature of harbors. Within this context, we recommend the Mean Shift Clustering (MSC) algorithm for efficient point cloud data segmentation, as endorsed by

Cariou (2022). By not requiring pre-defined parameters, MSC adapts seamlessly to data structure and density. Prioritizing density over proximity, Mean Shift effectively segments individual navigational elements, without the computational complexity of deep learning methods. The segmentation of point clouds is enhanced by accumulating and merging scans from multiple time points and perspectives. This approach improves the differentiation of distinct features such as large ships and harbor walls. However, it's important to verify the temporal consistency of accumulated point clouds to effectively filter out dynamic objects. Inconsistent measurements should be assigned lower weights or discarded, ensuring that the final dataset is reliable and representative of the static environment.

4.4 Bounding Box Estimation

After segmenting the point cloud, a geometric analysis of each segment can be conducted to estimate the dimensions and global positions of objects. This analysis is essential for identifying potential navigational hazards by accurately locating close objects. A bounding box is constructed around each segment, with the geometric center of the cuboid serving as the object's center. This method ensures accurate positioning for comparison with ENC features as it accounts for abstract reconstructions, e.g. S-101 maps buoys as points.

4.5 Object Identification

To classify objects from segmented point cloud data, we utilize and modify the classification framework developed by Yoshioka (2017) for maritime domain. In this framework, multiple weak classifiers are used to encode point cloud characteristics. Each of these classifiers is simple yet targets specific, subtle features of objects. By combining several such classifiers, the system gains robustness and efficiency, generating a detailed feature vector that captures essential characteristics of each object cluster.

Subsequently, Yoshioka use the Real AdaBoost algorithm (RAB) to compute all probability scores for each cluster, rating its alignment each of the S-101 object classes. Notably, the RAB algorithm enhances classification accuracy by iteratively refining its approach, correcting previous errors, and adjusting the influence of each classifier based on their performance. By training the classifier on labeled examples of objects such as buoys, beacons, vessels, and landmasses, the network learns to accurately classify unseen segments of point cloud data.

We recommend the dataset from Jin (2022) for training our classifiers, driven by its relevance to the maritime domain and its integration of LiDAR with GNSS for enhanced object detection. Jin also demonstrate the effectiveness of the dataset in identifying and tracking applications based on maritime environment perception, making it a suitable choice for our application. This dataset, proven in both simulative and real-world settings, ensures our object classifier reliable performance in diverse harbor scenarios.

While machine learning (ML) algorithms achieve impressive results on object identification tasks, the application to the dynamic and irregular maritime domain can result in crucial misclassifications. Hence, the use of ML must be carefully balanced with the need for reliability in safety-critical decision-making processes. It is crucial to confirm that the deployment of ML does not compromise the dependability of the object identification as safety is the top priority.

4.6 Object Localization

To put the data from the LiDAR into global context, the DGPS and IMU data are integrated, allowing for an absolute positioning of the retrieved objects. Building on Thompson (2019), this process involves transforming the objects relative positions, as determined by LiDAR, into a global coordinate system for accurate georeferencing and integration with ENCs. Illustrated in Figure 3, the procedure harmonizes data from the LiDAR's local coordinate system L and the DGPS receiver's local coordinate system G. The position of the center of the bounding box in LiDAR coordinates, $\vec{p}_L$, is given by

$$\vec{p}_L = \begin{pmatrix} r * \cos(\varphi) * \sin(\theta) \\ r * \cos(\varphi) * \cos(\theta) \\ r * \sin(\varphi) \end{pmatrix} \tag{1}$$

with r being the radial distance from LiDAR to the geometric center of an object's bounding box OC, φ the elevation angle and θ the azimuth in the east-north-up (ENU) coordinate system. This transformation aligns the LiDAR data within a three-dimensional space, facilitating subsequent adjustments.

Next, the system accounts for the spatial displacement between the LiDAR and DGPS systems, given by only a shift vector $\vec{d} = (d_x, d_y, d_z)$, as the relative orientation was calibrated when installing the sensors. The transformed position, $\vec{p}'_L$, yields:

$$\vec{p}'_L = \vec{p}_L + \vec{d} \tag{2}$$

This formula adjusts the LiDAR coordinates to align with the DGPS coordinate system G, ensuring that each object's position is accurately reflected in the local vessel context.

For global positioning, we combine the adjusted object's position with the ship's DGPS location, $\vec{p}_G$, to ascertain the object's global position, $\vec{p}_{Global}$. However, here we have to account for the rotational divergence of the DGPS from the global coordinate system using the orientation angles (α, β, γ). These angles denote the DGPS's orientation in relation to the global system. Orientation adjustment involves the rotational matrix $R = R_\gamma * R_\beta * R_\alpha$, where each matrix represents a rotation around each respective axis:

$$\vec{p}_{Global} = R * \vec{p}'_L + \vec{p}_G \tag{3}$$

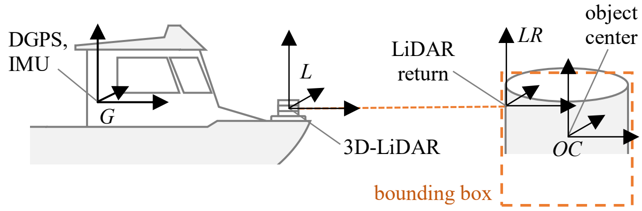

Figure 3: Illustration of the coordinate systems used for reconstructing the georeferenced position of the identified object's center point OC. This involves the transformation from coordinate system from the LiDAR (L) to the DGPS coordinate system (G).

Error propagation is also considered, where the total global error, E_G, is the sum of all absolute errors in positioning adjusted for the deviation in the orientation. Previous field tests gave error results below $0{,}6m$. The upper limit for deviation in object positioning is given by the absolute error in the DGPS position ($\pm 0{,}4m$), the position of the LiDAR returns ($\pm 0{,}1m$), and the object localization ($\pm 0{,}1m$). Additionally, the angular deviation ($\pm 1.0°$) compounds over the distance from DGPS to the object center (e.g. 50m), yielding:

$$|E_{DGPS}| + |E_L| + |E_{LR}| + \tan(\alpha_{dev}) * d < 1{,}5\ m \qquad (4)$$

4.7 Comparison between the detected and charted objects

After accurately determining the positions of objects using sensor data, objects are compared to those charted within the ENCs. As outlined in 4.6, translating the identified objects to the coordinate system utilized by the ENCs allows for precise matching. Additionally, verifying that the classification of each detected object aligns with the categories defined in the ENCs is necessary to enable accurate matching of the observed data with charted information.

Employing spatial analysis to the point cloud data, the dimensions and exact locations of detected objects are compared with their ENC counterparts. This comparison allows for the identification of discrepancies. Objects that do not align with the ENC data or that are present in reality but not charted, are carefully recorded. While these are the most important deviations to consider, we also record discrepancies in class and in shape. In each step the comparison is performed by defining maximum deviation thresholds that are based on the accuracy of our sensor system, while also considering the distance towards the object and the probability score of the classifier. This step is crucial for maintaining the integrity and accuracy of ENCs, while also considering system limitations, bridging the gap between observed maritime conditions and charted representations. By checking and refining the in-situ conditions and comparing to ENCs, this proactive identification and recording of discrepancies ensures that ENCs remain a reliable tool for safe and efficient harbor navigation.

Discrepancies foreseen to pose a potential navigational risk are documented in a structured format compliant with the S-101 standard. Findings are reported through a dedicated data base, designed to ensure near real-time updates and accessibility to various maritime stakeholders. This data base acts as a centralized platform for disseminating the supplemented ENCs, promoting collaborative efforts to address navigational hazards.

This methodical and algorithm-based process guarantees that ENCs are continuously verified and updated to reflect the current maritime conditions accurately. Implementing a data base that adheres to maritime regulations, such as the S-100 series by the IHO, ensures that updates to ENCs are standardized, making them universally interpretable by maritime navigation systems worldwide. This structured approach helps to minimize the risk of navigational errors and enhances maritime safety by providing accurate and up-to-date chart data to all maritime stakeholders.

5. EVALUATION

To assess the effectiveness and reliability of the proposed ENC refinement framework, a comprehensive evaluation process is essential. This chapter details our approach to systematically assess the framework's performance through field tests and metric-based evaluations, ensuring practical validity and alignment with maritime safety and accuracy requirements.

5.1 Field Tests with a Test Vessel

For practical evaluation, we equip a test vessel with a high-resolution 3D LiDAR, DGPS, and IMU and navigates predefined routes. Damm et al. (2022) advocate for Traffic Sequence Charts (TSCs) as a tool to standardize test procedures, ensuring all navigational challenges, from static obstacles to dynamic maritime changes, are accounted for. We adopt the TSCs to the maritime domain to design various maritime scenarios under controlled conditions and allow for reproducibility. The TSCs dictate the sequence of maneuvers, obstacle engagement, and navigation tasks, providing a structured framework for data collection and analysis. Additionally, we advocate for a dual strategy to accurately establish a ground truth, integrating both highly accurate Realtime Kinematic (RTK) GPS measurements and official ENC data. This process verifies that the system's detection and positioning capabilities are within the required error margins. Simultaneously, comparing sensor-derived data with official ENCs serves a twofold purpose: firstly, it benchmarks the system's performance against the established references provided by the hydrographical office. Secondly, it identifies discrepancies within ENCs themselves, spotlighting areas where updates or refinements are necessary. By incorporating regulatory considerations into the evaluation framework, the research aligns with established maritime safety protocols, ensuring that the findings and proposed system enhancements are both scientifically valid and practically applicable.

5.2 Evaluation Metrics

To effectively evaluate the performance of the proposed sensor system, precise test metrics are essential. These metrics reflect on the system's capabilities under varied conditions, while also relating to the derived system requirements, allowing a comprehensive assessment of the system's efficacy. The focus lies on object detection, aiming for a high reliability to guarantee that all significant maritime objects are correctly identified and can be matched against the ENCs.

Additionally, the accuracy of object positioning is analyzed, with LiDAR sensors anticipated to offer high accuracy. The total deviation of the object positioning is expected to remain below one and a half meters according to Equation (4). This assessment is crucial for pinpointing and rectifying inaccuracies in ENCs, directly catering to the needs for object verification and deficiency detection. High precision in object positioning significantly enhances the reliability and validity of the ENC refinement process and warrants rigorous verification.

Similarly, classification accuracy and robustness in identifying objects are essential for correctly incorporating relevant information into the ENCs.

However, these test metrics should not only reflect the system's performance in ideal conditions but also consider the challenges posed by dynamic maritime environments and adverse weather conditions. By carefully analyzing these metrics during field tests, a basis for evaluating the system's performance can be established. This approach ensures that the developed solution meets the set requirements and contributes to enhancing the safety and efficiency of maritime navigation. Incorporating RTK GPS calibrations and ENC data into the ground truth assessment further supports the demand for regulatory compliance, guaranteeing that reported objects are aligned with international maritime standards.

6. CONCLUSION

This work underscores the need for verifying the accuracy and reliability of ENCs to enable and support the future MASS projects. We propose a systematic approach, integrating high resolution 3D LiDAR, DGPS, and IMU data, alongside the strategic application of TSCs for structured field testing. Thereby we create a framework for ENC verification, deficiency detection, and chart refinement. The incorporation of both RTK GPS calibration and official ENC data for ground truth establishment ensures robust evaluation of navigational discrepancies nearly in real-time. This work not only highlights the potential for significant improvements in maritime safety but also emphasizes the importance of stakeholder collaboration and regulatory compliance in the advancement of navigational systems. The findings of this study advocate for the integration of sensor data with ENCs, paving the way for improved accuracy, reliability, and autonomous maritime navigation.

This research should be used as a foundation for further development and real-world application in maritime safety systems, particularly in automating and refining the process of ENC verification and updating. However, its effectiveness is contingent on the precision and reliability of the sensor equipment and the environmental conditions under which data collection occurs. The approach might face limitations in extremely adverse weather conditions or in highly dynamic maritime environments where the rapid movement of objects poses challenges to detection and classification. Future work should focus testing and validating the proposed concept in practice to provide further insights into the topic.

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REFERENCES

Cariou, C., Le Moan, S., & Chehdi, K. (2022). A novel mean-shift algorithm for data clustering. IEEE Access.

Damm, W., et al. (2018). A formal semantics for traffic sequence charts. Principles of Modeling: Essays Dedicated to E. A. Lee on the Occasion of His 60th Birthday.

Delobel, L., Aufrère, R., Debain, C., Chapuis, R., & Chateau, T. (2018). A real-time map refinement method using a multi-sensor localization framework. IEEE T-ITS.

German Aerospace Center. (2022). Closing conference for the presentation of the results of the SciPPPer project.

Guan, K., Shi, C., Wu, S., & Xu, T. (2010). Generation of Electronic Nautical Chart data for assessment of navigational safety in harbor and waterway design. In TransNav Journal.

Haghbayan, et al. (2018). An efficient multi-sensor fusion approach for object detection in maritime environments. In 2018 IEEE ITSC.

International Hydrographic Organization. (2018). S-100: Universal Hydrographic Data Model.

International Hydrographic Organization. (2021). MASS PT Work Plan (MASSPT5-3). Maritime Autonomous Surface Ships (MASS) Navigation Project Team (PT).

Karetnikov, V., Ratner, E., & Ageeva, A. (2017). Introduction of the automated hydrographic survey systems for creation of electronic nautical charts of internal waterways in Southern Africa. In 2017 IEEE AFRICON.

Lin, J., et al. (2022). Maritime environment perception based on deep learning. IEEE T-ITS.

Moosbauer, S., König, D., Jäkel, J., & Teutsch, M. (2019). A benchmark for deep learning based object detection in maritime environments. In IEEE CVPR Workshops.

Pirillo, P. (1999). A versatile, portable and low cost computerized data logging and charting system compatible with electronic nautical charts. In Oceans' 99. MTS/IEEE.

Qi, X., Fu, W., An, P., Wu, B., & Ma, J. (2020). Point Cloud Preprocessing on 3D LiDAR data for Unmanned Surface Vehicle in Marine Environment. In 2020 IEEE ICIBA.

Rife, J., & Xiao, X. (2010). Estimation of spatially correlated errors in vehicular collaborative navigation with shared GNSS and road-boundary measurements. In ION GNSS.

Schmidt, V., & Reed, S. (2018). Autonomous navigation on (US) nautical charts. In 2018 CHC.

Tang, W., Liu, E., Hao, Y., Huang, A., Wang, Z., & Wu, J. (2023). An Effective Way of Constructing Static Map Using 3D LiDAR for Autonomous Navigation in Outdoor Environments. IEEE Sensors Journal.

Thompson, D., Coyle, E., & Brown, J. (2019). Efficient LiDAR-based object segmentation and mapping for maritime environments. IEEE Journal of Oceanic Engineering.

Yoshioka, M., et al. (2017). Real-time object classification for autonomous vehicle using LIDAR. IEEE ICIIBMS.

Wang, B., Lan, J., & Gao, J. (2022). LiDAR filtering in 3D object detection based on improved RANSAC. MDPI Remote Sensing.