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Towards Certifiable Autonomous Local Public Transport on Waterways

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Towards Certifiable Autonomous Local Public Transport on Waterways

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Abstract. Autonomous and remotely operated vessels are poised to transform maritime mobility, logistics, and research. This paper presents the MS Wavelab, a comprehensive research platform for intelligent, certifiable, and resilient autonomous surface vessel (ASV) operation in coastal and inland waterways. We introduce a layered navigation framework that integrates sensor fusion, machine learning, and rule-aware path planning to achieve robust situational awareness (SA) and collision avoidance (COLAV) in dynamic maritime environments.

To address the lack of domain-specific training data, we curate a high-quality dataset of over 50,000 annotated images from 10,000 hours of video footage collected in real-world operations. This supports a camera-LiDAR fusion pipeline for visual object detection and distance estimation using YOLO-based models. For connectivity, we develop a hybrid communication architecture that combines 5G cellular and Starlink LEO satellite networks. By applying supervised learning models for bandwidth and handover prediction, we achieve stable, low-latency communication essential for teleoperation and high-resolution media streaming.

Our system architecture adopts a certification-oriented design, extending type-approved integrated navigation systems with autonomous modules while aligning with emerging international regulatory frameworks such as the IMO MASS Code. Together, these components enable safe, real-time decision-making and remote control in constrained and variable environments like the Kiel Fjord. The MS Wavelab serves as a scalable, modular platform to advance the state of the art in autonomous maritime systems and accelerate their real-world deployment.

1 Introduction

Advances in autonomy are driving a transformative shift in the maritime industry. Autonomous ships improve safety, efficiency, and sustainability in maritime transport by reducing human error, optimizing routes, and lowering operational costs.

Thousands of maritime incidents of various severity are reported in Europe every year. Notably, incidents involving passenger vessels have steadily increased in recent years [1]. Human error remains the leading cause, contributing to over 80% of all accidents at sea [25]. Autonomous and semi-autonomous vessel systems have the potential to drastically reduce these risks by providing continuous perception, rapid reaction, and rule-compliant navigation, thereby enhancing the safety of crews, passengers, and goods.

However, autonomy in the maritime domain introduces complex challenges. It demands reliable situational awareness, intelligent navigation, and secure communication, all while complying with evolving regulatory standards. In particular, safe and certifiable autonomy must be achieved without compromising operational performance or adaptability to changing maritime conditions.

In addition to being safe, autonomous vessels must operate efficiently. Optimal route planning minimizes fuel consumption and travel time while complying with international regulations such as COLREGs. These decisions must be made based on high-quality environmental perception, which in turn relies on rich datasets and robust multi-sensor fusion. As in other domains of artificial intelligence, the availability of diverse, labeled, and domain-specific data is a cornerstone of effective model development. A central enabler for this research is the **MS Wavelab**—a 21-meter, 8-meter wide twin-hull research catamaran purpose-built for the development and validation of autonomous and remote-control maritime systems. See Fig. 1. Its electric propulsion system offers precise programmatic control, while its modular sensor frame enables easy deployment of perception and communication hardware. The vessel's dual hulls accommodate server racks for high-performance onboard computation and storage. With certification for inland waterways, the Wavelab uniquely bridges real-world experimentation with research-grade infrastructure.

Our system design encompasses five key aspects—comprehensive datasets, robust situational awareness, adaptive path planning, reliable remote control, and a certification-oriented architecture—which collectively enable the development of safe, efficient, and certifiable autonomous local public transport. Since its maiden voyage in 2022, the MS Wavelab has conducted numerous research missions along the Kiel Fjord, continuously collecting environmental, vessel, and communication data. These missions have produced a rich dataset of over 50,000 manually verified visual annotations of maritime traffic, enabling the training of deep learning models for object detection and digital behaviour modeling. Robust situational awareness is achieved by fusing inputs from radar, AIS, GPS, LiDAR, and multiple camera systems through a real-time modular pipeline. To interpret complex maritime scenes, we employ frameworks like SV-NBA and NSA for anomaly detection and vessel behavior modeling, supported by predictive algorithms such as eCPA for accurate trajectory forecasting.

Path planning is handled by a hybrid approach combining predictive and reactive strategies, implemented in the RoboWaveLab framework. This integration enables intelligent trajectory generation that adapts to dynamic encounters and ensures safe navigation under COLREGs constraints. To support remote control and high-bandwidth operations, MS Wavelab utilizes a hybrid communication system consisting of multi-operator 5G cellular networks and Low Earth Orbit (LEO) satellite links such as Starlink. We deploy LSTM- and CNN-based models for bandwidth and handover prediction to ensure reliable communication for teleoperation and media streaming in challenging environments, such as near-shore and inland waterways. Finally, the navigation system is developed with a certification-oriented design, extending the proven SYNAPSIS NX Integrated Navigation System (INS) with autonomous control modules. This approach aligns with emerging standards from the IMO MASS Code and DNV classification rules, accelerating the path toward operational approval.

In summary, this paper presents a holistic architecture for certifiable maritime autonomy, built upon a real-world testbed, rigorous data pipelines, AI-driven situational modeling, and hybrid connectivity. The MS Wavelab serves as a scalable research and development platform to advance autonomous maritime systems toward real-world deployment.

2 Design

2.1 Sensor Suite and System Architecture

In the development of autonomous local public transport on inland waterways, the integration of sensor systems is essential to achieve reliable and certifiable navigation. The MS Wavelab is equipped with a range of sensors: X-band and millimeter-wave radar, RGB cameras, a forward-facing LiDAR, and an

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Figure 1: The research vessel MS Wavelab stationary (left) and during a test drive on Kiel Fjord (right).

AIS receiver. Additionally, IMU sensors provide motion estimation, while detailed digital sea chart data provides a static foundation for the vessels surroundings.

A crucial component of the perception system is the array of RGB cameras, providing a vital 360° perspective around the MS Wavelab. These cameras are used for real-time marine object detection and tracking leveraging a YOLO-based framework, identifying and monitoring various relevant targets on the waterway. Depth estimation is performed directly on the 2D camera images, yielding an approximate distance for detected objects, which is particularly valuable for targets potentially outside the effective range of the forward-facing LiDAR. Alongside depth, the bearing of detected objects is also calculated. This processed camera data, which includes object identity, estimated depth, bearing, and tracking information, is then prepared for integration with other sensor modalities.

Sensor data is distributed through a hybrid infrastructure that combines ROS2 and MQTT, serialized primarily in JSON format, with some binary data for high-throughput sensors. Synchronization is achieved using server clocks and timestamps, although precise synchronization (e.g., via NTP/PTP) is not yet implemented. Given the differing update rates across sensors, from AIS (low frequency) to cameras and radar (higher frequency), the fusion pipeline employs temporal buffering and alignment strategies that favor recency over strict synchronization. This ensures that the most up-to-date information drives decision-making.

The sensor system is organized in stages to manage data flow as shown in Fig. 2. AIS and IMU data are directly received via NMEA messages, while camera data undergoes real-time YOLO processing before being enriched with LiDAR distance information. Radar data already includes existing object tracking and clustering, particularly from the X-band radar. The mmWave radar provides raw point clouds that are subsequently integrated. These sensor outputs are then combined in the fusion pipeline to generate an enriched perception of the surrounding environment.

2.2 Sensor Fusion

The design of the fusion pipeline includes several modular services, each running as a stateless unit except for the final fusion step, which tracks previous detections as part of the merging logic. Sensors provide unique contributions in different scenarios and therefore each detection is to be prioritized over others based on different parameters such as distance, sensor stability, visibility, weather, and other contextual factors such as environmental conditions. Thus, a notable feature of the system is its reliance on a dynamic real-time decision-making framework. For example, LiDAR is used for precise distance measurements for close-range objects, while radar is employed for short to long-range detection and tracking, and AIS provides critical long-range awareness of vessel positions. These decisions are represented as a rule-based algorithm to merge new detections with existing targets, however contrary to statistical approaches like Kalman filters, this algorithm relies on basic conditions based on distance and bearing as well as detection type. Further information (if available) like course-over-ground, speed-over-ground and estimated objects dimensions may be used as a secondary source for the fusion, but rather serve as a verification than a condition. The fusion system integrates these multiple sources to create a robust and cohesive map of the environment, providing situational awareness and aiding in safe navigation. Manual evaluation of the resulting fused targets show successful merging mostly of AIS and radar detections, or sea chart and radar detections. In some situations it was also possible to have targets consisting of radar, sea chart, LiDAR and camera information. Upcoming trips with the MS Wavelab will now allow us to collect data to refine the parameters of said fusion rules as well as to set up a system of scenarios to measure the accuracy in a more sophisticated manner.

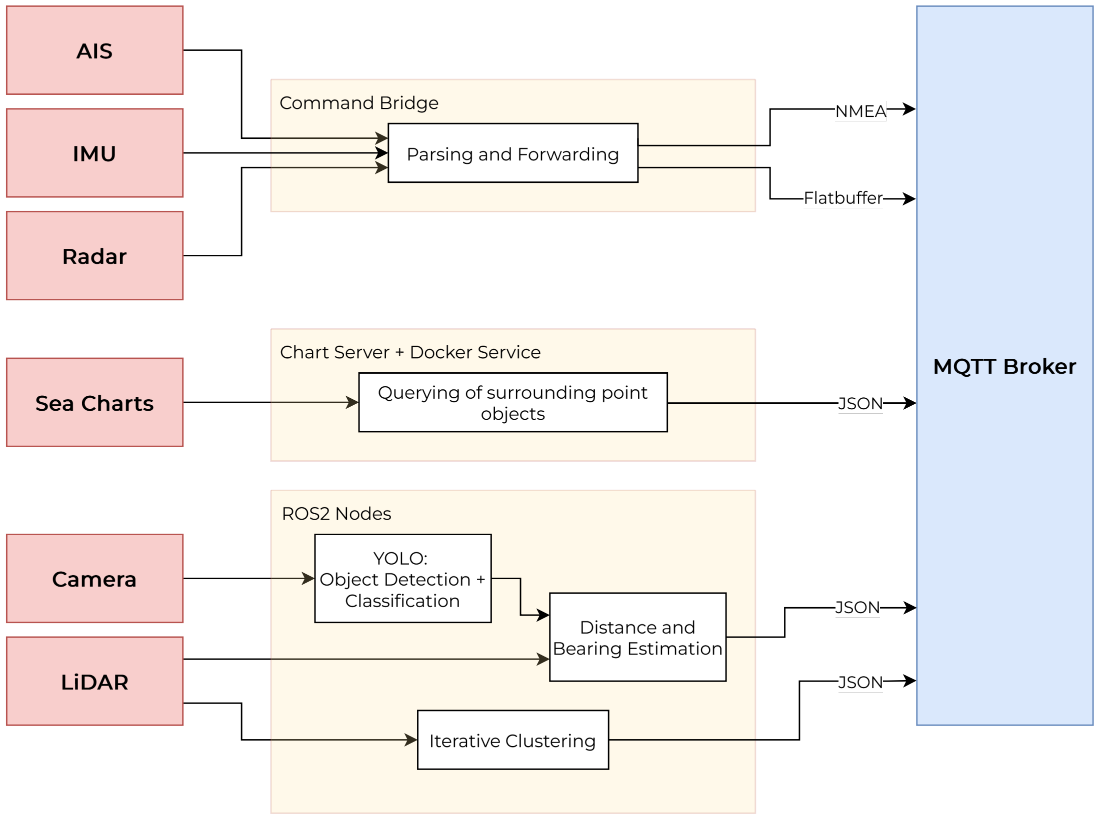


Figure 2: Sensor data processing pipeline.

The camera and LiDAR fusion pipeline is an area of ongoing development. Currently, the system uses camera-based YOLO object detection to provide bounding boxes for detected objects. See Fig. 3 Extrinsic calibration between the camera and LiDAR is then utilized to project the LiDAR point cloud into the image plane. Depth estimation for a detected object is refined by considering the LiDAR points that fall within its corresponding bounding box, allowing for a more accurate distance measurement when the object is within the LiDAR's effective range.

The fusion system itself is developed with the objective of creating a complete, sound, and robust system with a high degree of modularity. This modular design enhances system flexibility and allows for independent testing and updates to each component. To ensure that our system will meet certifiable standards, the telemetry network plays a critical role. Various system metrics (see Fig. 4) can be collected during test trips of the vessel, and these data points will be used to further analyse the soundness of the fusion logic, as well as ensuring stable and low-latency processing to minimize any delays for the upcoming path planning. Current telemetry data show an average fusion time of around 80ms (from the incoming message to the output of a fused target), however these results are preliminary as the underlying data sets are not yet representative enough. This does not mean the fusion pipeline is bounded by 12 targets per second, as manual testing, without rigorous benchmarking, suggests that, due to concurrency, the system can handle around 120 to 150 target updates per second in practice. The infrastructure supports both production and development environments, enabling partial replay of real-world tours in harbors or fjords for testing purposes. Through the application of continuous integration (CI) processes, updates can be handled more easily and upcoming versions of the algorithms can be compared more extensively.

2.3 Data and Datasets

Effective and reliable object detection in the unique environment of inland waterways, such as the Kiel fjord, necessitates a dedicated, domain-specific dataset that accurately reflects real-world conditions and relevant object classes. Unlike standard computer vision benchmarks, the targets encountered by autonomous passenger vessels—including specific types of ships, boats, navigation markers, and infrastructure unique to this domain—are not adequately represented. To build this crucial resource, data collection

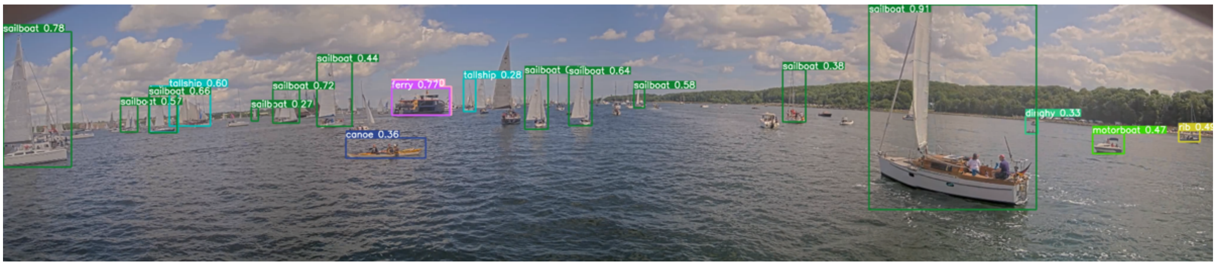


Figure 3: Bounding boxes for detected objects on the Kiel fjord during sailing event.

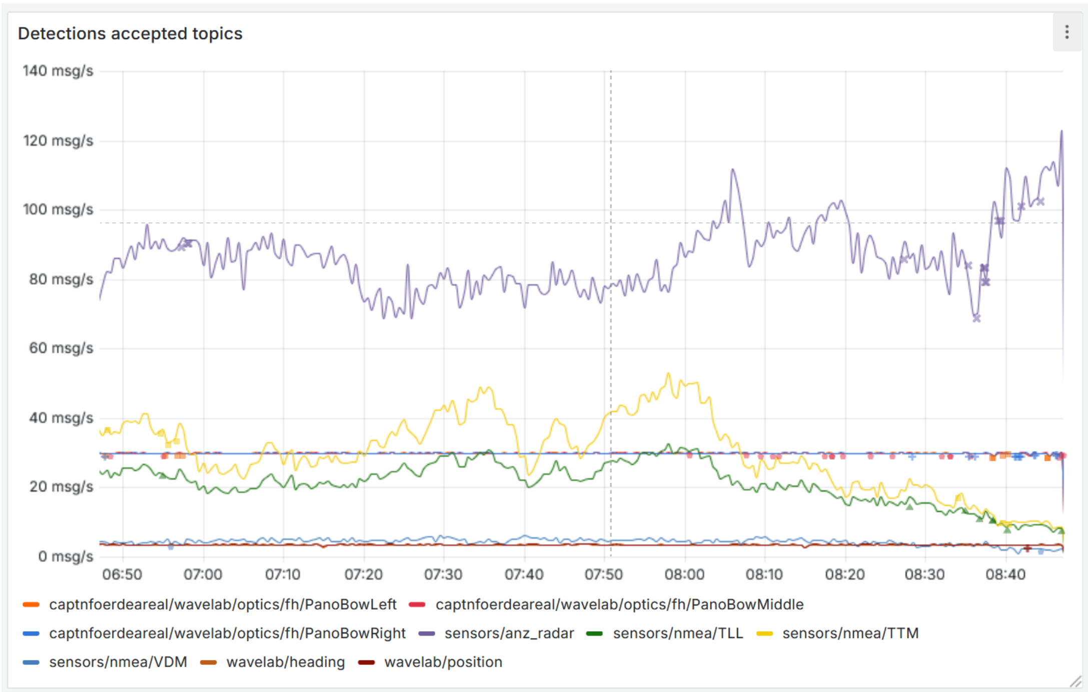
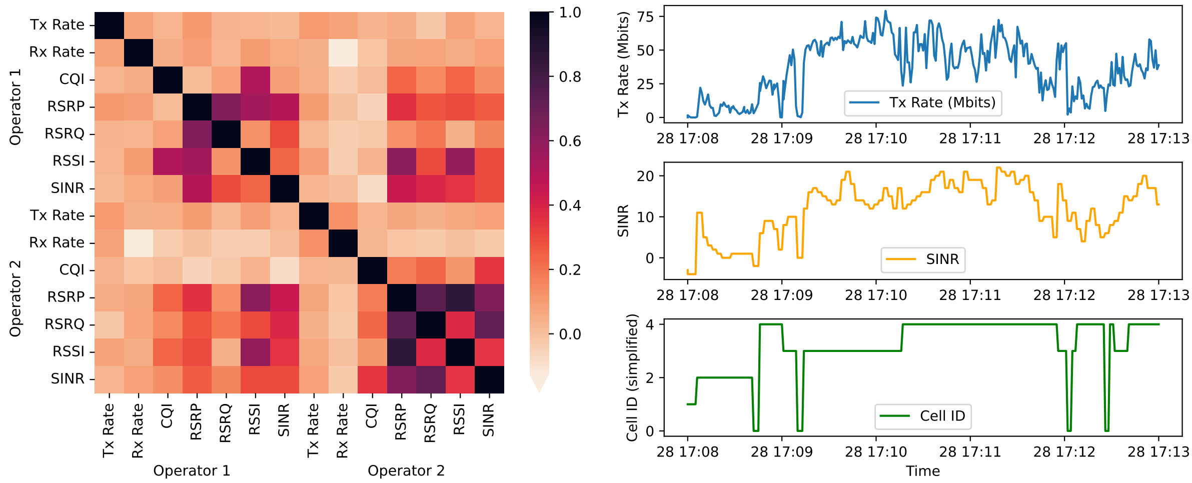


Figure 4: Visualization over time showing the frequency of incoming detections per MQTT topic.

commenced on the MS Schwentine and has been primarily conducted on the MS Wavelab itself, directly capturing the challenging and diverse operational scenarios faced by these vessels during their regular routes. This extensive effort has gathered over 10,000 hours of video footage from 6 cameras. From this vast pool of raw material, we curated a high-quality training dataset comprising 50,000 images. This image dataset is rich in variability, encompassing a wide spectrum of traffic situations, different weather phenomena, and varying times of day, ensuring the trained model is robust to real-world unpredictability encountered in the Fjord. Within these images, approximately 300,000 maritime objects belonging to 32 distinct classes were initially semi-automatically classified and marked with precise bounding boxes. We then conducted a manual review of all annotations to ensure high accuracy. Crucially, this meticulously annotated image dataset is currently utilized for training the YOLO-based object detection network, forming the foundation for robust visual perception of marine objects in this challenging environment. The trained model achieves an overall mAP@0.5 of 0.60 and mAP@0.5:0.95 of 0.37 on the test set. However, the performance varies significantly across classes due to data imbalance. For instance, seamark objects achieve an mAP@0.5 of 0.85, while rare classes like dredger reach only 0.37. This highlights the challenge of detecting infrequently seen objects compared to commonly observed classes.

The use of machine learning in wireless networking has increased significantly in recent years. However, existing 5G datasets primarily focus on the performance and characteristics of land-based vehicular networks. Therefore, they do not present the unique challenges of the coastal maritime domain, such as large distances from base stations, dynamic sea states, and changing interference from water surface



(a) 5G Operator Correlation (b) Effects of Handover Events

Figure 5: With the Fjord5G dataset, we analyze cellular network coverage in the Kiel Fjord: Fig. a shows operator correlation across 5G routers. Fig. b depicts how handover events affect uplink bandwidth.

reflections and nearby vehicles. We collected the Fjord5G dataset [1] for coastal maritime connectivity and next-generation wireless network research [10]. We conduct an extensive measurement campaign with the MS Wavelab and the MS Gaarden over 12 months using two mobile network operators and four 5G routers equipped with external maritime-grade and default antenna arrays. Our GPS-labeled cellular data measurements cover the network conditions encountered in coastal and near-shore regions of the Kiel Fjord. Using the Fjord5G dataset, we analyze network coverage, correlations between mobile network operators, and bandwidth across LTE, 5G Non-Standalone (NSA), and 5G Standalone (SA) network deployments in Figure 5. Initial analysis reveals key challenges, such as varying bandwidth and handover events, which we address using bandwidth and handover prediction algorithms based on Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) models [29, 28, 12, 13].

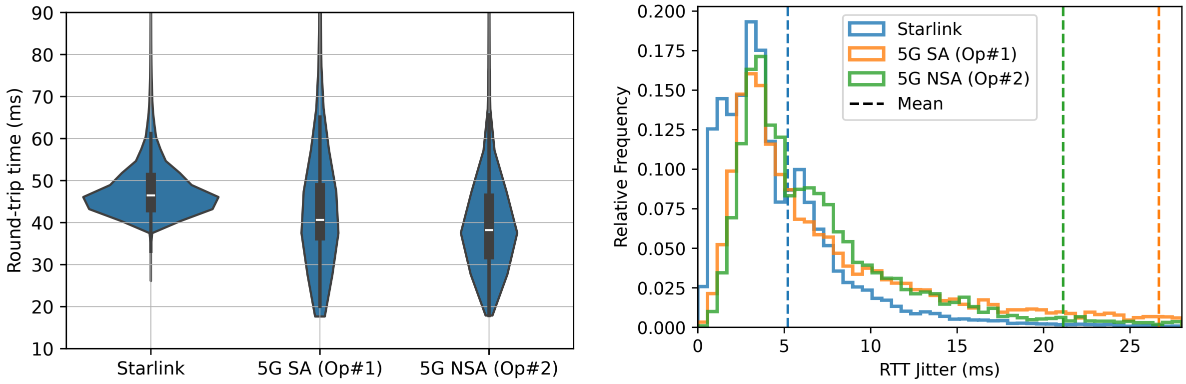
Additionally, limited cellular network coverage of rivers and canals, such as the Kiel Canal, makes remote operations challenging for cellular networks. We utilize a Low Earth Orbit (LEO) satellite network system, specifically Starlink, to increase coverage of areas with limited cellular coverage near inland waterways. To test the performance of Starlink, 5G SA, and 5G NSA cellular networks for coastal maritime teleoperated vessel control, we collect detailed network measurements for bandwidth, directional latencies, jitter, see Figure 6, as well as telemetry from Starlink terminal and 5G routers in the FjordLink dataset [2] [11]. Our initial analysis shows that LEO satellite networks are essential to avoid network outages in inland waterways. While 5G networks provide higher throughput and lower latencies when a high signal strength is available, they also suffer from frequent handovers, high latency spikes, and low bandwidth. To address these challenges, we use LEO satellites to provide a backup network that has slightly higher mean latency and lower worst-case latency while offering a stable uplink bandwidth that is lower than cellular networks. By analyzing each network individually, we aim to automatically switch between available links from different mobile network operators or technologies, thereby providing a seamless experience for remote control and monitoring use cases.

2.4 Navigation

Autonomous maritime navigation represents a significant technological advance that promises increased safety, efficiency, and operational capabilities for sea transport. Achieving reliable autonomy requires the seamless integration of several core technological components, primarily focusing on perceiving the environment and making safe navigational decisions. This section delves into two fundamental pillars that support Autonomous Surface Vessel (ASV) operation: (i) robust situational awareness (SA); (ii) and intelligent path planning combined with Collision Avoidance (COLAV).

[1] Available as open source: https://github.com/ds-kiel/Fjord5G

[2] Available as open source: https://github.com/ds-kiel/FjordLink



(a) Round-trip Time (RTT) Comparison (b) Jitter Comparison

Figure 6: We show the performance of Starlink and 5G networks in the FjordLink dataset: Fig. a gives the distribution of RTT values between networks, while Fig. b focuses on the comparison of jitter values.

Developing a robust navigation system capable of adapting to changes in the maritime environment hinges on the integration of three key capabilities: enhanced perception of the surroundings, a reliable SA mechanism to detect abnormal navigational behaviour, and an intelligent navigation module. This navigation module must be able to initiate appropriate responses—such as COLAV maneuvres or proactive path replanning—to ensure safe and efficient operation. Together, these components enable resilient and adaptive autonomous navigation, as illustrated in Figure 7.

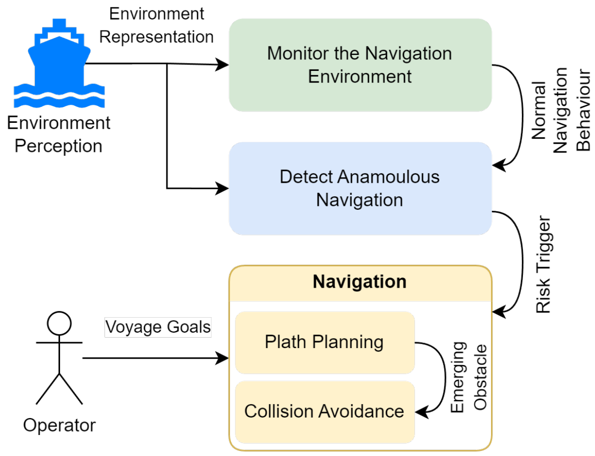


Figure 7: Conceptual overview of a situational awareness-driven navigation framework for autonomous surface vessels, comprising environmental monitoring, anomaly detection, and adaptive navigation actions including path planning and collision avoidance.

In Section 2.4.1, we discuss the critical role of SA, describing our approach based on the Surface Vessel Nautical-Behaviour Analysis (SV-NBA) framework [20], and the subsequent refinement to build a comprehensive Nautical Situational Awareness (NSA) framework [21]. These frameworks serve as an *observer layer* that provides a comprehensive understanding of the vessel's navigation environment. The cognitive awareness of the observer layer serves as input for evaluating the subsequent *control layer* for safe autonomous navigation.

Section 2.4.2 explores the methodologies adopted for path planning and COLAV, integrating both RoboWaveLab [18] and the enhancement of the traditional Closest Point of Approach tool, extended as enhanced CPA (eCPA) [22] to ensure safe and efficient trajectory planning and navigation in dynamic maritime environments.

Combined, these two layers form the cognitive engine that allows the MS Wavelab vessel to navigate (semi-)autonomously and interact safely with other emergent traffic.

Section 2.4.3 examines the certification-oriented design of the autonomous navigation system, leveraging state-of-the-art integrated navigation technologies and established testing standards to reduce overall system complexity and thereby accelerate qualification and operational deployment.

2.4.1 Situational Awareness SA is a fundamental prerequisite for the safe and efficient operation of ASVs, particularly in complex and dynamic maritime environments such as the Kiel Fjord [20]. It encompasses the perception of environmental elements, the comprehension of their meaning in relation to operational goals, and the projection of their future status [21]. In the maritime context, achieving robust SA involves not only detecting static obstacles and waterway boundaries using onboard sensors (as detailed in Section 2.2) but also critically understanding the dynamic behaviour of other vessels and predicting their future actions to enable proactive decision-making and COLAV[20, 22]. Failures in SA are a major contributor to maritime incidents, often due to human error in conventional navigation [21].

The AIS serves as a cornerstone for maritime SA, providing real-time data on vessel identity, position, speed, and course [20, 21]. Although mandated for larger vessels and widely used, AIS data alone is insufficient and presents challenges, including potential inaccuracies, transmission gaps, and vulnerability to manipulation [20, 21]. Therefore, three categories of additional features were extracted from the preprocessed AIS, including (i) static, (ii) ship, (iii) ship-to-ship features. The preprocessing of AIS data is a multistep process to prepare the raw signals for analysis and modeling, cf. [20]. Initially, raw AIS messages were decoded according to the NMEA 0183 standard, and the trajectories were retrieved by grouping messages by MMSI of the vessel and chronologically sorting them, appending static information from the vessel. Afterwards, trajectory assembly refined these paths through geofencing to exclude data outside the Kiel Fjord and from berthed vessels, segmenting trajectories into distinct trips based on stops and observation gaps, removing outliers to ensure data quality, and applying smoothing and interpolation techniques to create continuous representations of vessel movement despite irregular signaling intervals. Finally, feature extraction augmented the basic kinematic data AIS (position, speed, course, turn rate) with derived features such as acceleration and angular differences, environmental context features such as minimum distances to waterways, restricted areas, marinas and shorelines, and temporal features including cyclical encodings for time and categorical representations for seasons and parts of the day.

These preprocessing steps are vital to improve the reliability of understanding the surrounding environment. Subsequently, a Gaussian Mixture Models (GMMs) spatio-temporal clustering is used over a Denoising Autoencoder (DAE) latent space representation to create Digital Shadows (DSs) of vessel behaviour, cf. [19]. These models represent normative patterns and can be used for efficient storage and comparison online with real-time observations [21].

Deviations from these learned models can indicate anomalies or unexpected behaviour, significantly enhancing SA by highlighting potentially hazardous situations that require attention [21]. See Figure 8.

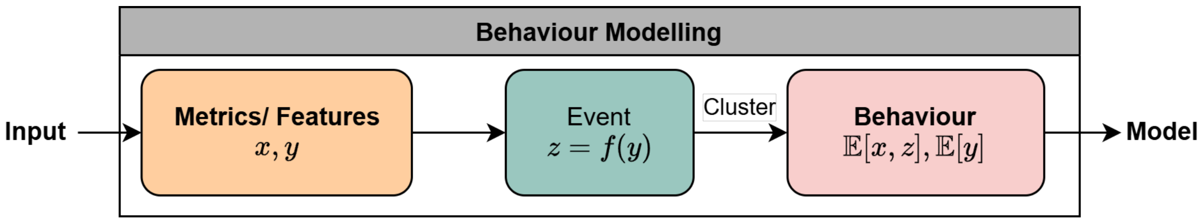


Figure 8: Overview of the behaviour modelling pipeline used to construct Digital Shadows (DS) for vessel activity. Extracted features from preprocessed AIS trajectories (x, y) are used to identify events $(z = f(y))$, which are subsequently clustered. These clusters are then used to model typical vessel behaviours through statistical expectations $\mathbb{E}[x, z], \mathbb{E}[y]$. This process enables the identification of normative patterns, serving as a reference for detecting deviations and anomalies that support enhanced Situational Awareness.

Furthermore, advanced maritime SA extends to predicting future trajectories and intentions of surrounding vessels. Traditional methods like the Closest Point of Approach (CPA) calculation, while standard, often rely on simplistic assumptions of constant velocity and course, which may not hold true in dynamic encounter situations. See Figure 9.

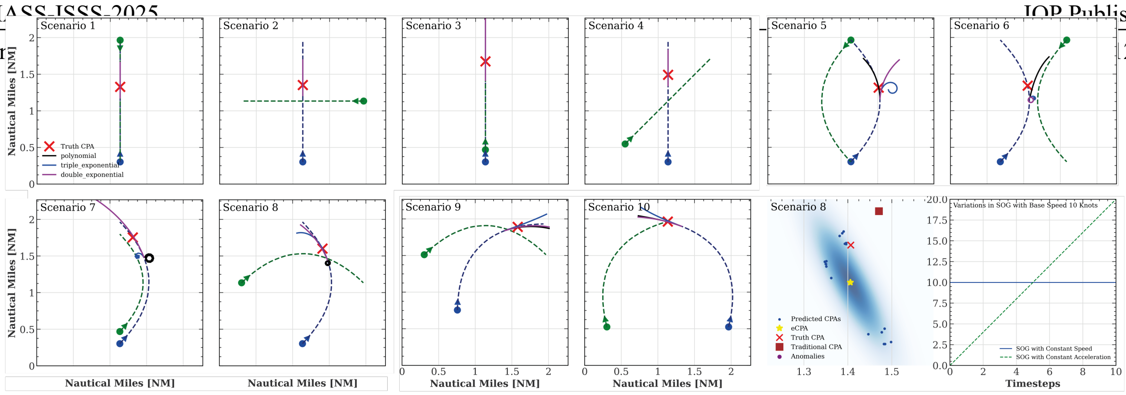


Figure 9: Ten encounter scenarios with non-constant speed-over-ground (SOG) and course-over-ground (COG), demonstrating the improved accuracy of estimating the closest point of approach.

Enhanced methods, such as the approach Enhanced Closest Point of Apporach (eCPA), incorporate trajectory prediction models and probabilistic risk assessment, considering potential changes in vessel behaviour and environmental factors to provide a more robust estimate of collision risk [22]. Integrating such predictive capabilities into the SA system allows ASV to anticipate potential conflicts well in advance and plan more effective avoidance maneuvers.

In summary, achieving comprehensive SA for autonomous vessels requires a multifaceted approach. It involves robust sensor fusion that provides the input for (i) analysing historical data to model and understand normative behaviours through SV-NBA framework; (ii) learning effective representation of the input data, to enable robust modelling and analysis as available using NSA framework deployed on Automatic Identification System (AIS) data; (iii) furthermore, NSA—and the more advanced FEAST—framework provide the foundations for DS-based anomaly detection; (iv) and employing predictive models like eCPA to anticipate future states and assess risks effectively.

This cognitive understanding of the environment is crucial to allow subsequent stages of navigation, namely path planning and Collision Avoidance.

2.4.2 Path Planning Path planning is a critical component of autonomous navigation systems for maritime vessels, responsible for determining optimal trajectories that ensure safe, efficient, and rule-compliant operation [18]. In the context of ASVs operating in dynamic environments like the Kiel Fjord, path planning must address unique challenges, including the heterogeneous marine traffic, the dynamic nature of the maritime environment, and compliance with maritime regulations such as COLREGs [22, 18].

Maritime path planning approaches can be broadly categorized into three main strategies: predictive, reactive, and hybrid [18]. Predictive strategies utilize prior information about the environment to plan end-to-end paths. Among these, the A* algorithm and its variant D* are deterministic grid-search methods that evaluate adjacent cells using a cost map based on combined metrics of distance and heuristics [18]. In contrast, heuristic approaches, such as Rapidly Exploring Random Tree (RRT), employ a sampling-based method that builds a random tree to discover suitable paths while respecting predefined constraints, including angle and velocity limitations [18]. These predictive methods excel in planning comprehensive routes but may struggle with computational efficiency in highly dynamic environments.

Reactive strategies, on the other hand, focus on immediate obstacle avoidance by considering only the next action based on real-time sensor data [18]. The Dynamic Window Approach (DWA) operates by selecting appropriate translational and rotational velocities within a local area around the vessel to maximize an objective function that balances progress toward the goal, distance to obstacles, and vessel velocity [18]. Similarly, the Velocity Obstacle (VO) method utilizes relative velocities and positions of nearby objects to determine safe trajectories by defining sets of velocity obstacles indicating potential collisions [18]. These reactive approaches offer computational efficiency and real-time adaptability but may not produce globally optimal paths.

To overcome the limitations of individual approaches, we developed *RoboWaveLab*, a hybrid strategy that combines predictive and reactive methods for risk-aware path planning, cf. [18]. In such systems, a predictive planner first generates a collision-free global path considering static obstacles and projected positions of dynamic vessels, often using the Closest Point of Approach (CPA) calculation, or eCPA for improved collision estimation [22]. When an obstacle enters a defined critical zone (empirically set as 100 meters), a reactive planner activates to perform dynamic collision avoidance maneuvers [18]. Once the obstacle leaves an extended safety zone (empirically set to 200 meters), the system reverts to the predictive algorithm to reevaluate the route [18].

Smoothing generated trajectories is critical to ensure navigability, especially given the limited maneuverability of maritime vessels [18]. In *RoboWaveLab*, we achieved this goal through iterative corner smoothing that identifies shortcuts while maintaining safe distances from obstacles. Afterwards, the application of Bézier curves transforms the trajectory into a parametric curve with fine granularity, resulting in smooth directional changes that facilitate easier navigation [18].

We evaluated the path planning algorithms of *RoboWaveLab* in various simulation-based maritime scenarios, focusing on key performance metrics: (i) computational runtime, (ii) path length, (iii) suboptimality (i.e., deviation from the ideal direct path), (iv) minimum distance to obstacles (as a measure of collision risk), (v) and the number of course changes (indicating path smoothness) [18]. These metrics provide a comprehensive basis for assessing the trade-offs between safety, efficiency, and computational feasibility in autonomous maritime navigation.

In the context of the MS Wavelab, the *RoboWaveLab* path planning system integrates with the NSA module —described in Section Section 2.4.1— to leverage the comprehensive environmental understanding for effective trajectory generation. This integration ensures that path planning decisions are informed by accurate perception of the surroundings, reliable prediction of other vessels' movements, and proper risk assessment, ultimately enabling safe and efficient autonomous navigation in complex maritime environments [22, 18].

2.4.3 Certification-Oriented Design of the Autonomous Navigation System The verification and certification of autonomous navigation systems represents a significant challenge. It is, however, imperative for acquiring operational permits and ensuring safe navigation. Regulatory frameworks for automated and autonomous vessels are currently being developed internationally for both seagoing and inland waterways. In order to ensure the certification of the autonomous navigation system of the MS WaveLab, the system design incorporates a combination of certified core technologies, enhanced components, as well as new technologies. The test vessel MS Wavelab is equipped with a complete SYNAPSIS NX Integrated Navigation System (INS). Synapsis NX is a state-of-the-art INS that combines all the necessary navigation sensors and systems in a modular, user-centered design to make bridge operations safer and more efficient. Navigators benefit from superior situational awareness, decision support, reduced distraction, and therefore a lower risk of human error. The INS incorporates radar, ECDIS, and conning, along with essential components such as health monitoring, centralized data and alarm management, target handling, and automatic control. The INS has been comprehensively certified, type-approved, and field-proven.

Compared to inland waterway vessels, SOLAS vessels are subject to performance standards for navigation systems and components. The major standards for performance requirements, methods of testing, and required test results are as follows: **IEC 60945** [5]: General requirements for maritime navigation and radiocommunication equipment and systems, **IEC 61162** [6] Digital interfaces for navigational equipment. **IEC 61924-2** [26] Operational and performance requirements for modular Integrated Navigation Systems, **IEC 61174** [7] Electronic Chart Display and Information System (ECDIS), **IEC 62288** [8]: Presentation of navigation-related information, **IEC 62388** [9] Shipborne radar and **ISO 11674** [35],**ISO 16329** [36], **IEC 62065** [27]: Standards for autopilot and track control systems. The familiar core of the INS is extended in autonomous navigation systems to include automatic collision avoidance functions, integration of optical sensors, dynamic situational awareness, and improved alarm management. This approvable standard creates the structure to include additional requirements and functions in specific projects, such as performing safety and risk analyses, enabling automated functions, and defining different levels of IT security.

The IMO is working on the International Code of Safety for Maritime Autonomous Surface Ships (MASS Code), which is currently available as a draft version and is being finalized in working groups. The IMO plans for the MASS Code to become mandatory by 2032. In January 2025, the classification society DNV published the documents "Rules for Classification Ships Part 6 Additional Class Notations, Chapter 12 Autonomy and Remote Operation" [16] and the "Class Guideline DNV-CG-0264 Autonomous and Remotely Operated Vessels" [15].

The combination of certified navigation components with innovative technologies reduces system complexity and accelerates both qualification and operational deployment in real-world environments.

The approach defined by the IMO MASS Code and the guidelines of classification societies aligns with the general methodology of systems engineering. This process results in the creation of key documents such as the system concept, the Concept of Operation (ConOps), the Operational Design Domain (ODD), the Operational Envelope, and the risk and safety assessment. Based on these documents, design specifications and system requirements are formulated and allocated to the respective system elements. In parallel, a verification and validation strategy must be developed. For both the overall system and each in-

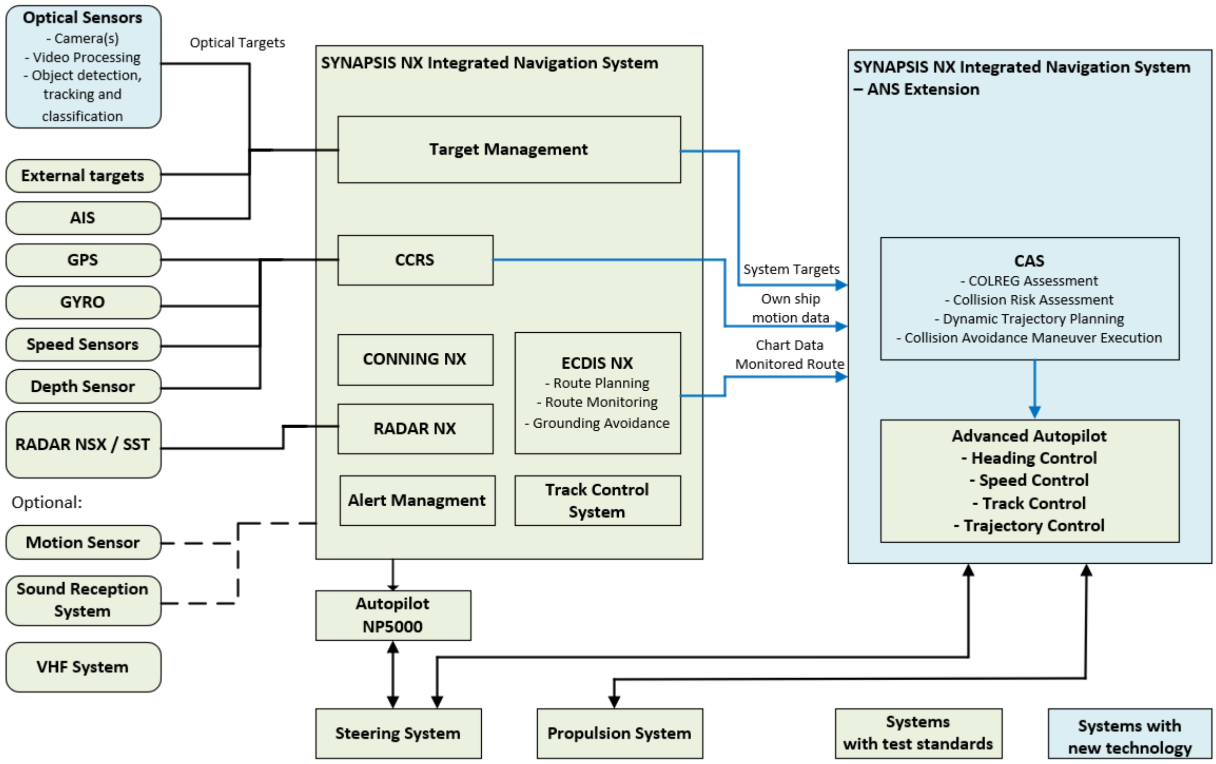


Figure 10: Wavelab overview Integrated Navigation System

dividual system element, a verification plan and corresponding test documentation are required. Existing performance test standards for SOLAS vessels provide a valuable foundation in this context. However, it is necessary to conduct an analysis to determine which functions can be covered and qualified using these standards. For system elements that incorporate new technologies—such as intelligent optical sensors, COLREG-compliant situational assessment, or dynamic trajectory planning and execution—entirely new verification plans and test documents must be developed. Figure 10 illustrate a categorization of elements into new technologies and existing test standards. The analysis also reveals that familiar system elements may include new functionalities or that the performance requirements for MASS systems exceed those defined by current standards. For example, radar standards include specifications for automatic target acquisition and tracking, while autopilot standards define functions for track control and heading control. Practical experience gained from trials with the MS Wavelab in the Kiel Fjord demonstrates that these standards are insufficient in terms of test coverage and performance thresholds to fully verify a MASS system. Nevertheless, they provide a solid baseline for defining minimum requirements. Therefore, existing verification and validation documents for established technologies must be reviewed and adapted to the specific MASS system and its system requirements. This analysis and revision process is significantly easier than creating entirely new documentation—especially considering that the entire process and its outcomes are subject to review by certifying and approving authorities. Recognized documentation facilitates collaboration with external stakeholders and contributes substantially to acceptance and regulatory approval.

2.5 Remote Control Technology

Fig. 11 illustrates the data flow on the autonomous maritime vessel Wavelab, focusing on what data is processed and how systems on board communicate with a central server and land-based platforms. The main data sources are:

- **Anschütz system** processes and transmits sensor data and control commands using the specified protocol of the National Marine Electronics Association (NMEA). The sensor data includes AIS, radar, GPS, IMU, nautical sensors, etc.

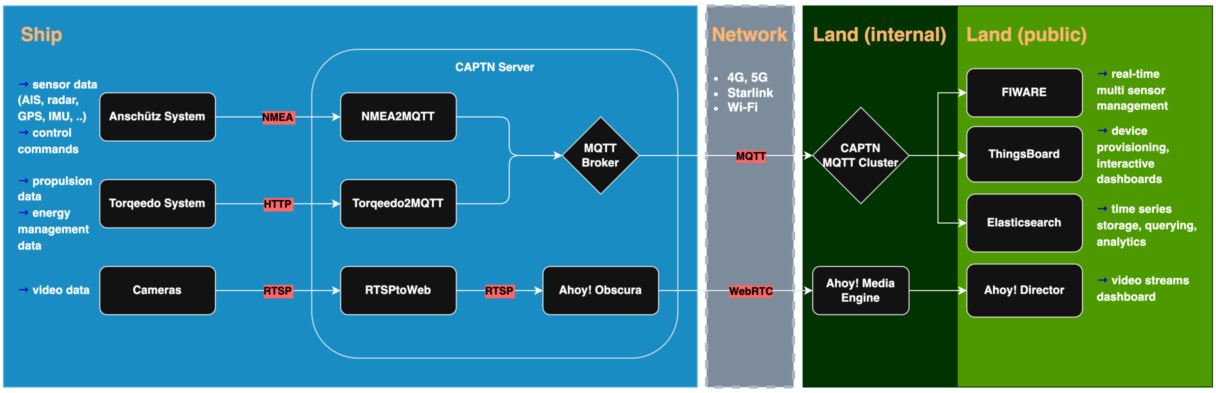


Figure 11: Wavelab data flow overview

- **Torqeedo system** is a propulsion system that also provides energy management data. It communicates using the HTTP protocol.
- **The cameras** produce Real-Time Streaming Protocol (RTSP) streams.
- **The network telemetry** is transmitted via MQTT from the 5G routers and the Starlink terminal.

All incoming data flows into the CAPTN server, which acts as the central processing unit of the ship. Within the CAPTN server, the first components convert the raw inputs into MQTT messages, which are aggregated by the MQTT broker and broadcast to all subscribers. The video streams are handled by the open source package RTSPToWeb [32], which relays the streams to Ahoy! Obscura— this service wraps RTSP in a WebRTC-compatible format and manages the WebRTC signaling. In addition to WebRTC, we also test video streams based on Media over QUIC (MoQ) for scalable and low-latency video feeds [30]. We develop a new Quality of Experience (QoE) telemetry framework called FrameTrace to analyze and adapt MoQ video streams in real-time using a light-weight controller [14].

The MQTT broker is synchronized with a land-based cluster that acts as a centralized data distribution system, providing broader access to the ship's data. Downstream, these data flows are consumed by external platforms with web user interfaces (WebUIs) such as FIWARE (a context broker for real-time multi-sensor management) [23], ThingsBoard (an IoT platform for device provisioning and interactive dashboards) [37], and Elasticsearch (a time series storage and analytics system) [17]. The Ahoy! Media Engine, a central part of the AhoyRTC stack [2], acts as a selective forwarding unit, ingesting WebRTC streams and routing them to Ahoy! Director, a web-based dashboard where viewers can independently monitor all video streams from the ship.

Data is transmitted from the ship to land using available **public wireless networks** in Fig. 12. The vessel has multiple cellular network modems that operate within LTE, 5G non-standalone, and 5G standalone, see Fjord5G dataset for details [10]. It can use different mobile network operators within overlapping coverage areas. The other options include LEO satellite links (e.g., Starlink) and coastal-area Wi-Fi access points, see FjordLink dataset for details [11]. Rules in the ship's network topology assign different flows to network interfaces.

The main production network is divided into three internal subnetworks: (a) a research network for sensor data distribution and experimental systems; (b) a restricted network for low-capability devices with only 10 Mbit Ethernet interfaces; and (c) a network for intercom systems and the rearview camera. These subnetworks are permitted to communicate with each other. Users can access only the bridge network, which itself has no connectivity to the Internet. Both the vessel and the remote control center have external connectivity routed through a centralized firewall located at the data center. This firewall is equipped with antivirus and intrusion detection capabilities, and it also manages VPN-based remote access for authorized users. Additionally, the communication link between the vessel and the data center uses WireGuard to form an encrypted tunnel. On the research network, the WireGuard VPN and a QUIC-based VPN are used [31].

2.5.1 Data transmission The described data flows are typical of IoT telemetry and consist of frequent, small payloads of serialized sensor or status data, for which lightweight messaging protocols like MQTT

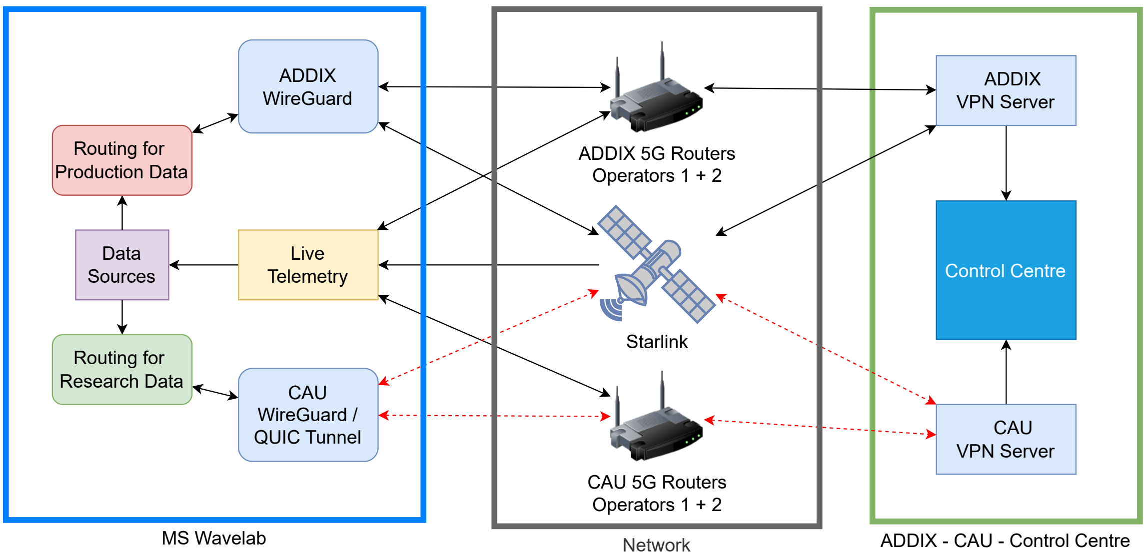


Figure 12: Overview of the available network interfaces on the Wavelab

provide a reliable, ultra-low latency transmission [3]. Real-time media flows are persistent and high-bandwidth streams. Several key technologies are used:

- **WebRTC**: a browser-native protocol that enables sub-second, peer-to-peer streaming.
- **Media over QUIC**: a simple and scalable low-latency media delivery solution for ingest and distribution of media.
- **GStreamer**: an open source multimedia framework for building flexible processing pipelines [24]. This flexibility comes at the cost of transcoding latency. GStreamer is used for critical video feeds; all other streams are handled by the Ahoy! services without transcoding.
- **Deep Reinforcement Learning (DRL)**: AI-driven models that utilize WebRTC feedback and dynamically adjust encoding bitrate, framerate, and resolution to maximize QoE while avoiding congestion. The detailed architecture and workflow are described in [34].
- **Bandwidth Prediction based on Supervised Learning**: We use LSTM-based models to predict available downlink and uplink bandwidth in cellular networks. Predicting the capacity and channel quality of each network allows us to intelligently route traffic to the optimal network interface. When cellular networks suffer low signal strength, we automatically route critical functions to the Starlink network. We present our *BandSeer* [3] and *CapAware* [4] models in previous publications, see Figures 13 and 14 for evaluation of our models [12, 13].

2.5.2 Latency Since the sender and receiver clocks cannot be perfectly synchronized in a real-time communication (RTC) scenario, round-trip time (RTT) is used instead of one-way latency. RTT is measured in four ways:

(a) **WebRTC RTT**: reported by WebRTC feedback from the viewer's browser back to the ship. Depending on network coverage, this RTT can range within the Kiel Fjord from about 30 ms up to 3 s. More details are provided in [33].

(b) **Media over QUIC**: We measure glass-to-glass latency using our FrameTrace QoE telemetry measurement framework [14]. FrameTrace provides individual encoding, propagation, and decoding latencies on a per-frame basis to optimize the end-to-end video streaming pipeline, see detailed latency analysis in the paper for select video resolutions and bitrates.

[3] Available as open source: https://github.com/ds-kiel/BandSeer
[4] Available as open source: https://github.com/ds-kiel/CapAware

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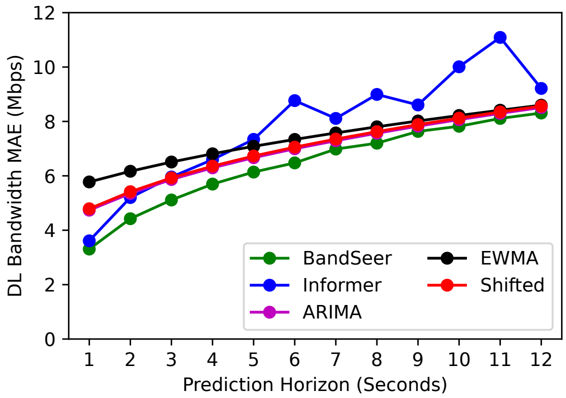
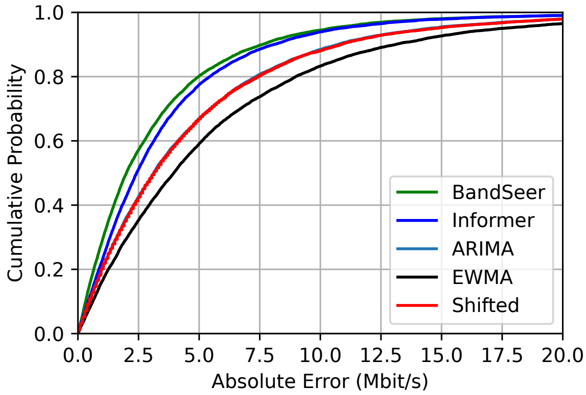
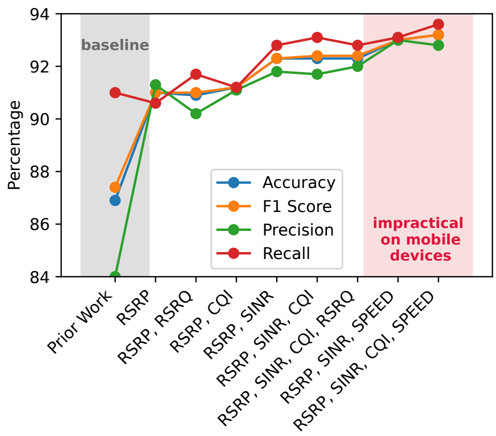


(a) Download Bandwidth Prediction

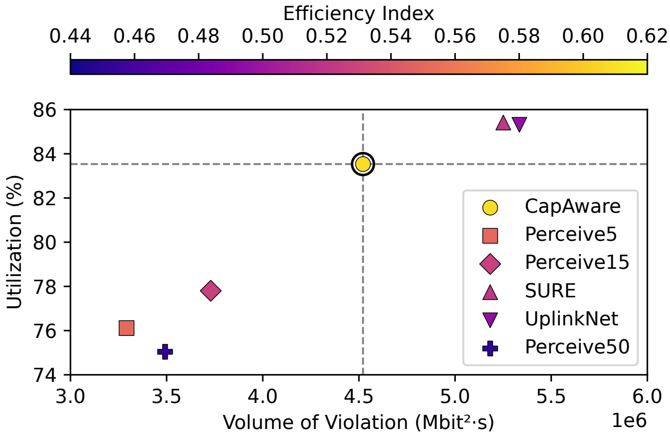


(b) Cumulative Probability for errors of models

Figure 13: We evaluate the performance of our BandSeer model against statistical and deep learning baselines: Fig. a compares the BandSeer model against baselines across prediction horizons of up to 12 seconds, while Fig. b compares models in terms of the cumulative distribution of absolute errors.



(a) CapAware Handover Prediction



(b) CapAware Uplink Bandwidth Prediction

Figure 14: We evaluate the performance of our CapAware model against deep learning baselines: Fig. a provides an ablation study of the CapAware against a baseline, while Fig. b compares the CapAware in terms of efficiency index (e.g., the ratio of network utilization to capacity violation) against baselines.

(c) **Ahoy! Media Engine RTT**: measured via an ICMP ping from the ship to the Ahoy! Media Engine's onshore TURN server with a typical range of 40 ms to 70 ms.

(d) **Two-Way Active Measurement Protocol (TWAMP)** [4]: We use TWAMP to measure the latency and jitter of available links. While typical median RTT ranges are around 46 ms for Starlink and 40 ms for cellular networks, 99th percentile latencies of Starlink provide much lower values at 82 ms compared to cellular networks at 1376 ms, see Fjord5G and FjordLink datasets for more details [10, 11]. Without automatic network routing, critical operations, such as video streams, suffer from very high latency spikes, especially on inland waterways, such as the Kiel Canal.

When streams are transcoded on board, an additional 100 ms to 400 ms of delay is introduced, depending on hardware acceleration and transcoding complexity [33]. Despite this overhead, transcoding enables the transmission of high-resolution H.265 camera feeds (e.g., from Reolink cameras installed on the ship) that browsers cannot decode natively.

3 Conclusion

The successful realization of autonomous and remotely operated surface vessels hinges on the integration of robust navigation intelligence, reliable communication infrastructures, and certifiable system architectures. In this paper, we present the design and implementation of the MS Wavelab testbed, highlighting its layered cognitive navigation system, situational awareness capabilities, and adaptive path planning. Through a combination of predictive and reactive strategies, supported by behaviour modelling frameworks such as SV-NBA and NSA, the vessel is able to operate safely and intelligently within complex maritime environments like the Kiel Fjord.

Complementing the autonomy stack, our remote control and data transmission infrastructure ensures high availability and responsiveness under heterogeneous network conditions. By combining cellular 5G networks with LEO satellite connectivity (Starlink) and applying machine learning for bandwidth and handover prediction, we demonstrate a resilient hybrid communication system capable of supporting real-time control and video streaming, even in challenging inland waterway scenarios.

Importantly, our approach emphasizes certification-oriented design. By embedding proven, type-approved navigation systems such as Synapsis NX and extending them with modular autonomous capabilities, we align closely with emerging standards from IMO and classification societies. This integration provides a practical path toward operational qualification and compliance with future MASS regulations.

Together, these technological components form a cohesive ecosystem for autonomous maritime operations, bridging the gap between academic research, engineering practice, and regulatory requirements. The MS Wavelab serves as a living laboratory to accelerate innovation in smart shipping and lays the foundation for scalable, certifiable deployments in real-world scenarios.

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References

[1] European Maritime Safety Agency. *Annual overview of marine casualties and incidents 2024*. URL: `https://www.emsa.europa.eu/publications/reports/download/7981/5352/23.html`.

[2] AhoyRTC. `https://ahoyrtc.com/`. Last accessed: August 14, 2025.

[3] Bauyrzhan Amirkhanov et al. "Evaluating HTTP, MQTT over TCP and MQTT over WEBSOCKET for digital twin applications: A comparative analysis on latency, stability, and integration". In: *International Journal of Innovative Research and Scientific Studies* 8.1 (2025), pp. 679–694.

[4] Jozef Babiarz et al. *A Two-Way Active Measurement Protocol (TWAMP)*. RFC 5357. Oct. 2008. DOI: `10.17487/RFC5357`. URL: `https://www.rfc-editor.org/info/rfc5357`.

[5] International Electrotechnical Commission. *IEC 60945 – Maritime navigation and radiocommunication equipment and systems – General requirements*. Fourth edition, 2002-08. 2002.

[6] International Electrotechnical Commission. *IEC 61162 series – Maritime navigation and radiocommunication equipment and systems – Digital interfaces*. Edition 6.0, 2024-04. 2024.

[7] International Electrotechnical Commission. *IEC 61174 – Maritime navigation and radiocommunication equipment and systems – Electronic chart display and information system (ECDIS) – Operational and performance requirements, methods of testing and required test results*. Edition 4.0. 2015.

[8] International Electrotechnical Commission. *IEC 62288 – Maritime navigation and radiocommunication equipment and systems – Presentation of navigation-related information on shipborne navigational displays – General requirements, methods of testing and required test results*. Edition 3.0, 2021-12. 2021.

[9] International Electrotechnical Commission. *IEC 62388 – Maritime navigation and radiocommunication equipment and systems – Shipborne radar – Performance requirements, methods of testing and required test results*. Edition 2.0. 2013.

[10] Birkan Denizer, Nils Dohse, and Olaf Landsiedel. “Fjord5G: A Comprehensive 5G Dataset for Coastal Maritime Connectivity”. In: *2025 IEEE 101st Vehicular Technology Conference (VTC2025-Spring)*. 2025, pp. 1–5.

[11] Birkan Denizer, Nils Dohse, and Olaf Landsiedel. “FjordLink: Comparison of Starlink and 5G Networks for Teleoperated Vessel Control”. In: *LEO-NET: Proceedings of the Workshop on LEO Networking and Communication, held with the ACM SIGCOMM, 2025*. 2025.

[12] Birkan Denizer and Olaf Landsiedel. “BandSeer: Bandwidth Prediction for Cellular Networks”. In: *2024 IEEE 49th Conference on Local Computer Networks (LCN)*. 2024, pp. 1–8. DOI: 10.1109/LCN60385.2024.10639706.

[13] Birkan Denizer and Olaf Landsiedel. “CapAware: Capacity-Aware Uplink Bandwidth Prediction for Cellular Networks”. In: *2025 IEEE 50th Conference on Local Computer Networks (LCN)*. 2025.

[14] Birkan Denizer, Lasse Winkel, and Olaf Landsiedel. “FrameTrace: Frame-Level Telemetry for Media over QUIC”. In: *EMS: Proceedings of the Workshop on Emerging Multimedia Systems, held with the ACM SIGCOMM, 2025*. 2025.

[15] Det Norske Veritas. *Class Guideline DNV-CG-0264: Autonomous and Remotely Operated Vessels*. Updated guideline released in December 2024; entered into force on 1 January 2025. Forms the basis for the AROS class notations. 2024. URL: https://rules.dnv.com.

[16] Det Norske Veritas. *Rules for Classification – Ships Part 6 Additional Class Notations, Chapter 12: Autonomy and Remote Operation*. Published in the July 2024 edition of the DNV Rules for Classification of Ships. Entered into force on 1 January 2025. 2024. URL: https://rules.dnv.com.

[17] Elasticsearch. https://www.elastic.co/elasticsearch. Last accessed: August 14, 2025.

[18] Ghassan Al-Falouji, Tom Beyer, and Sven Tomforde. “From social robots to autonomous surface vessels’ navigation”. In: *2023 IEEE International Conference on Autonomic Computing and Self-Organizing Systems Companion (ACSOS-C)*. IEEE. 2023, pp. 59–64.

[19] Ghassan Al-Falouji, Christian Gruhl, and Sven Tomforde. “Digital shadows in self-improving system integration: a concept using generative modelling”. In: *2021 IEEE International Conference on Autonomic Computing and Self-Organizing Systems Companion (ACSOS-C)*. IEEE. 2021, pp. 166–171.

[20] Ghassan Al-Falouji et al. “A Framework for Surface Vessel Nautical-Behaviour Analysis towards Cognitive Situation Awareness”. In: *Proceedings of Conference on Cognitive and Computational Aspects of Situation Management (COGSIMA)*. Vol. 102. 2024, pp. 199–214.

[21] Ghassan Al-Falouji et al. “Enhancing Maritime Behaviour Analysis Through Novel Feature Engineering and Digital Shadow Modelling: A Case Study in the Kiel Fjord”. In: *International Conference on Architecture of Computing Systems*. Springer. 2024, pp. 97–111.

[22] Ghassan Al-Falouji et al. “Steering Towards Maritime Safety with True Motion Predictions Ensemble”. In: *2024 IEEE International Conference on Autonomic Computing and Self-Organizing Systems Companion (ACSOS-C)*. IEEE. 2024, pp. 7–12. DOI: 10.1109/ACSOS-C63493.2024.00021.

[23] FIWARE. https://www.fiware.org/. Last accessed: August 14, 2025.

[24] GStreamer. https://gstreamer.freedesktop.org/. Last accessed: August 14, 2025.

[25] Nermin Hasanspahić et al. “The Role of the Human Factor in Marine Accidents”. In: *Journal of Marine Science and Engineering* 9.3 (2021). ISSN: 2077-1312. DOI: 10.3390/jmse9030261. URL: https://www.mdpi.com/2077-1312/9/3/261.

[26] International Electrotechnical Commission. *IEC 61924-2:2012 (E) – Maritime navigation and radiocommunication equipment and systems – Integrated navigation system – Operational and performance requirements, methods of testing and required test results*. Specifies the minimum requirements for the design, manufacture, integration, methods of testing and required test results for an integrated navigation system (INS) to comply with IMO Resolution MSC.252(83). 2012.

[27] International Electrotechnical Commission. *IEC 62065:2014 – Maritime navigation and radiocommunication equipment and systems – Track control systems – Operational and performance requirements, methods of testing and required test results.* Specifies the minimum operational and performance requirements, methods of testing and required test results conforming to performance standards adopted by the IMO in Resolution MSC.74(69) Annex 2: Recommendation on Performance Standards for Track Control Systems. 2014.

[28] Alexandr Langolf, Sebastian Kühl, and Stephan Pachnicke. "Transfer Learning for Handover Prediction in 5G Maritime Vehicular Networks". In: *2024 19th International Symposium on Wireless Communication Systems (ISWCS).* 2024, pp. 1–5. DOI: 10.1109/ISWCS61526.2024.10639141.

[29] Alexandr Langolf and Stephan Pachnicke. "Handover Prediction for NSA 5G Systems in Maritime Environments using Machine Learning". In: *Mobile Communication - Technologies and Applications; 27th ITG-Symposium.* 2023, pp. 74–77.

[30] Suhas Nandakumar et al. *Media over QUIC Transport.* Internet-Draft draft-ietf-moq-transport-13. Work in Progress. Internet Engineering Task Force, July 2025. 93 pp. URL: https://datatracker.ietf.org/doc/draft-ietf-moq-transport/13/.

[31] Tommy Pauly et al. *Proxying IP in HTTP.* RFC 9484. Oct. 2023. DOI: 10.17487/RFC9484. URL: https://www.rfc-editor.org/info/rfc9484.

[32] RtspToWeb. https://github.com/deepch/RTSPtoWeb. Last accessed: August 14, 2025.

[33] Nikita Smirnov and Sven Tomforde. *Exploring the Dynamics of Data Transmission in 5G Networks: A Conceptual Analysis.* 2024. arXiv: 2404.16508 [cs.NI].

[34] Nikita Smirnov and Sven Tomforde. "Real-time rate control of WebRTC video streams in 5G networks: Improving quality of experience with Deep Reinforcement Learning". In: *Journal of Systems Architecture* 148 (2024). DOI: 10.1016/j.sysarc.2024.103066.

[35] International Organization for Standardization. *ISO 11674 – Heading control systems.* Edition 3, 2019-11. 2019.

[36] International Organization for Standardization. *ISO 16329 – Heading control systems for high-speed craft.* Edition 1, 2003-04-15. 2003.

[37] ThingsBoard. https://thingsboard.io/. Last accessed: August 14, 2025.