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Review

Maritime Autonomous Surface Ships: Architecture for Autonomous Navigation Systems

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Abstract: The development of Maritime Autonomous Surface Ships (MASS) has seen significant advancements in recent years, yet there remains a lack of comprehensive studies that holistically address the architecture of autonomous navigation systems and explain the complexity of their individual elements. This paper aims to bridge this gap by conducting a literature review that consolidates key research in the field and presents a detailed architecture of autonomous navigation systems. The results of this study identify several major clusters essential to MASS navigation architecture, including (1) autonomous navigation architecture, (2) decision-making and action-taking system, (3) situational awareness and associated technologies, (4) sensor fusion technology, (5) collision avoidance subsystems, (6) motion control and path following, and (7) mooring and unmooring. Each cluster is further dissected into sub-clusters, highlighting the intricate and interdependent nature of the components that facilitate autonomous navigation. The implications of this study are vital for multiple stakeholders. Ship captains and seafarers must be prepared for new navigation technologies, while managers and practitioners can use this architecture to better understand and implement these systems. Researchers will find a foundation for future investigations, particularly in filling knowledge gaps related to autonomous ship operations. This study makes a substantial contribution by filling a critical gap in the maritime literature, offering a detailed explanation of the elements within autonomous navigation systems.

Keywords: MASS; autonomous navigation; situational awareness; sensor fusion; collision avoidance; architecture

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1. Introduction

Over the last two decades, bridge sittings for navigators have gone through various changes, which explains the fast pace of new technologies [1]. In other words, the role of navigators has transformed into a more supervisory (planning) role, and the monitoring, execution and surveillance are taken by automated systems such as the autopilot and ARPA (Automatic Radar Plotting Aid) [1]. As exhibited in the following Table 1, the trend in maritime navigation technology significantly advanced over time and is still revolutionising. Thus, a huge amount of data is generated by ship sensors (onboard), databases and maritime services.

Recently, Maritime Autonomous Surface Ships (MASSs) arose to the surface and thus are expected to conduct remote-controlled operations including autonomous navigation. This topic has been widely addressed as a cornerstone in shipping automation, in both large prototype projects, small-size autonomous surface vehicles, and various research studies. MASSs have been largely investigated in academic peer-reviewed studies or in technical reports from industries and classification societies. Indeed, MASSs have gained attention recently with predictions for eventual industry adoption [2,3]. It is argued that a MASS has several benefits, for instance, it reduces human error, increases safety [4], and improves environmental protection, such as reduction of fuel consumption and GHG emissions, including air pollutants (through the advanced digitalisation and the ability to utilise software that improves the energy efficiency, optimising routes and speeds using advanced algorithms, reducing idling time, MASS can reduce GHG emissions, while the engine can be electrified and the alternative fuels can be used due to larger spaces), minimisation of waste, routes optimisation, and reducing oil spills or discharge [5–17], enhances economic and supply chain efficiency [17,18], and reduces collision risks [19,20]. MASS also lowers operational costs and supports sustainability [8,21]. Other studies indicated that MASS would also benefit ports in developing countries [22] and enhance military applications [23]. Recently, Yara Birkeland and ReVolt are two notable projects showcasing real-world applications of MASS. Yara Birkeland, developed by Yara and Kongsberg, is the world's first fully electric and autonomous container ship, designed to reduce emissions and alleviate road traffic congestion by replacing truck journeys with maritime transport. Similarly, ReVolt is a small-scale autonomous vessel used as a research platform to test autonomy in coastal short sea shipping, focusing on energy efficiency and safety in autonomous maritime operations [20].

Table 1. Trend in maritime navigation technologies and techniques.

Year	Technologies
1190	European Magnetic Compass
1266	Portulan Charts
1342	Mariner's Astrolabe, sandglass
1480	Mercator Nautical Chart
1570	Chip Log (Speed)
1646	Magnetic Variation
1722	Sextant
1798	Greenwich Mean Time
1874	National Almanac, Marine Chronometer
1950	LOP, LORAN-C, AIS
1958	Transit (Satellite Navigation)
1960	Radar, GPS
1980	Inertial Navigation, ARPA, OMEGA, echosounder, COLREG
1990	Global Navigation Satellite System (GNSS), Radio Wireless Telegraph, GMDSS
2010–2015	ECDIS, BNWAS, AIS, VTS
2016–2020	LIDAR, collision avoidance systems
2021–2025	Remote controlled and autonomous ships, advanced situational awareness technologies, VR/AR

The International Maritime Organisation (IMO) launched regulatory scoping for MASS conventions, highlighting gaps and suggesting a MASS code [24,25]. Projects such as MUNIN, AAWA, and AUTOSHIP have explored MASS prototypes [26–28], while classification societies (e.g., Lloyd's Register, DNV, CCS, Bureau Veritas) provided guidelines but lacked focus on communication needs [29–35]. Research, on the other hand, covered adoption factors [36], costs and benefits [37], Arctic competitiveness [38], navigator skills [39], cybersecurity [40], and automation tasks [41]. Additionally, studies examined manoeuvring [41], ecosystem value [21], and success factors [42]. Furthermore, MASS-specific functions and other issues were also addressed, e.g., control [43], risks [44], safety [45,46], technical challenges [47], autonomy [48], shore control centres [49], crew tasks [50], MASS navigation [4,51,52], system architecture [53], and design [54]. Various reviews addressed autonomy levels [5], collision avoidance [4], USV development [19,55,56], autonomous navigation [57], sustainability [58] and road map for MASS technologies [3,16,59,60]. Despite these efforts, few studies have focused on autonomous navigation, and none have developed a comprehensive architecture that serves as a one-stop resource, integrating and unifying the fragmented literature.

Given the introduction, this study aims to review the literature and assess the architecture of autonomous navigation systems in MASS, which are critical for their development and integration into the maritime industry, i.e., the research question is "What are the systems and subsystems that constitute the architecture MASS, and how do they function together to enable autonomous navigation".

This study contributes in two significant ways. First, it fills a gap in the literature by providing a holistic architecture that integrates various elements of autonomous navigation, acting as a one-stop resource for understanding these systems. Second, the study offers practical insights for stakeholders including researchers, shipowners, policymakers, and maritime technologists, enabling them to better prepare for the implementation of autonomous systems by understanding the complexities and interdependencies of the required technologies. Overall, this architecture serves as a framework for understanding how the autonomous navigation process works and its broader operational context.

The outline of this study is as follows. Section 1 provides the background and relevance of this research, identifying gaps in the literature and defining the objectives. Section 2 is the materials and methods, Section 3 is the result and discussion, which includes autonomous navigation architecture, decision-making and action-taking system, situational awareness and associated technologies reviews, sensor fusion technology, collision avoidance subsystems, database, motion control and path following, mooring and unmooring. Finally, Section 4 presents the conclusions and implications of the study.

2. Materials and Methods

This study reviews the literature through a semi-systematic literature review approach. First, sensitive search terms for titles and keywords were selected to collect a wide-ranging pool of studies and facilitate comprehensive analysis. Two search iterations were conducted to identify studies (i.e., academic peer-reviewed articles, conference proceedings, book chapters, and technical and industrial reports). The first combination included search terms related to MASS: (MASS OR "Maritime Autonomous Surface Ship" OR "Autonomous Ship"). The second combination included search terms related to the core of the review: "navigation": (navigation OR situational awareness OR collision avoidance OR control OR navigational sensors OR dynamic positioning OR COLREGs OR intelligent navigation OR path planning). The third combination included search terms related to "autonomy and automation": (Autonomous OR architecture OR remote control OR automated OR unmanned OR command OR algorithms OR artificial intelligence OR real-time). Scopus (www.scopus.com (accessed on 10 January 2024)) was the main database used for the search, in addition to Google (to search for technical reports). This ensured all-encompassing consideration of an assortment of literature. The search resulted in 732 studies; however, exclusion and inclusion criteria were established to minimise the number of studies. The inclusion and exclusion criteria for this review on autonomous navigation systems for MASS were defined as follows: The review includes articles published in English, covering empirical studies, systematic reviews, chapters, proceedings, and technical reports with clear and comprehensive data and methodologies. Only studies available in full text via academic databases, institutional access, or open sources were considered. The focus is on works directly related to MASS and the core topic of "autonomous navigation", ensuring methodological rigour and alignment with the study's purpose. Excluded are non-English articles, studies without accessible full texts, those lacking methodological rigour, generic MASS studies, irrelevant themes, and repetitive conference proceedings covered by peer-reviewed articles. The final selection comprised 162 (105 peer-reviewed articles, 18 reports, 23 conference proceedings, and 16 books or chapters) abridged studies that directly addressed the study's objectives. After collection of the included studies, a qualitative analysis was conducted in order to establish various themes and build the architecture in two stages: first, each author independently reviewed the studies; then, the authors synthesised the findings and resolved conflicting themes to minimise potential biases. On this basis, the authors constructed a comprehensive architecture for MASS autonomous navigation system, incorporating all necessary subsystems that enable ships to navigate and avoid obstacles autonomously or under the supervision of seafarers. The key clusters and subsystems that comprise autonomous navigation were built to address the complexity and fragmented nature of existing studies.

3. Results and Discussion

3.1. Autonomous Navigation Architecture

Autonomous navigation is achieved by training or programming the ship with the stored data about the vessel's behaviour in various sailing environments [61]. Different studies designed the autonomous navigation differently. Navigation is divided into obstacle detection and avoidance, navigation, guidance, and control (NGC), and motion control [4,52]. The MASS autonomous navigation is dependent on onboard computers that have software to make decisions in addition to sensor technologies that both enable situational awareness and collision avoidance systems [4,27,62–64]. Autonomous behaviour (navigation) banks on intelligent analytics that depend on machine learning algorithms in addition to the deep learning approach, which is, considering advances in machine learning, becoming a powerful technique for autonomy [61]. Machine learning and deep learning methods depend on advanced algorithms, which are an integral part of engineering applications. Deep learning (end-to-end learning) is predicted to shape the maritime industry when considering the large amount of performance and operation data generated by shipping [61].

In this scenario, the autonomous navigation architecture is rebuilt, and, in so doing, all the subsystems required to let the ship navigate and avoid obstacles on its own or at least under the supervision of seafarers are included. See the following Figure 1, which illustrates the autonomous navigation architecture that enables the understanding of how the autonomous navigation process works and its context.

The autonomous navigation system consists of decision-making and action-taking systems, which depend heavily on the situational awareness subsystem sensors that feed the obstacle detection and map representation and the local path planning as part of collision avoidance. The actions, once decided, are passed to the control system to control the motion of the ship and keep it on the designated path through the control of autopilot (steering and rudder) and machinery (propulsion) while considering the vessel's properties. This step is based on the actuators' reaction that executes the actions. The situational awareness, collision avoidance and control subsystems data and information come from different sensors. Data are large; therefore, they need to be fused through the sensor fusion technology and then stored in the internal database. The following sections provide a detailed presentation and explanation of the whole autonomous navigation subsystem.

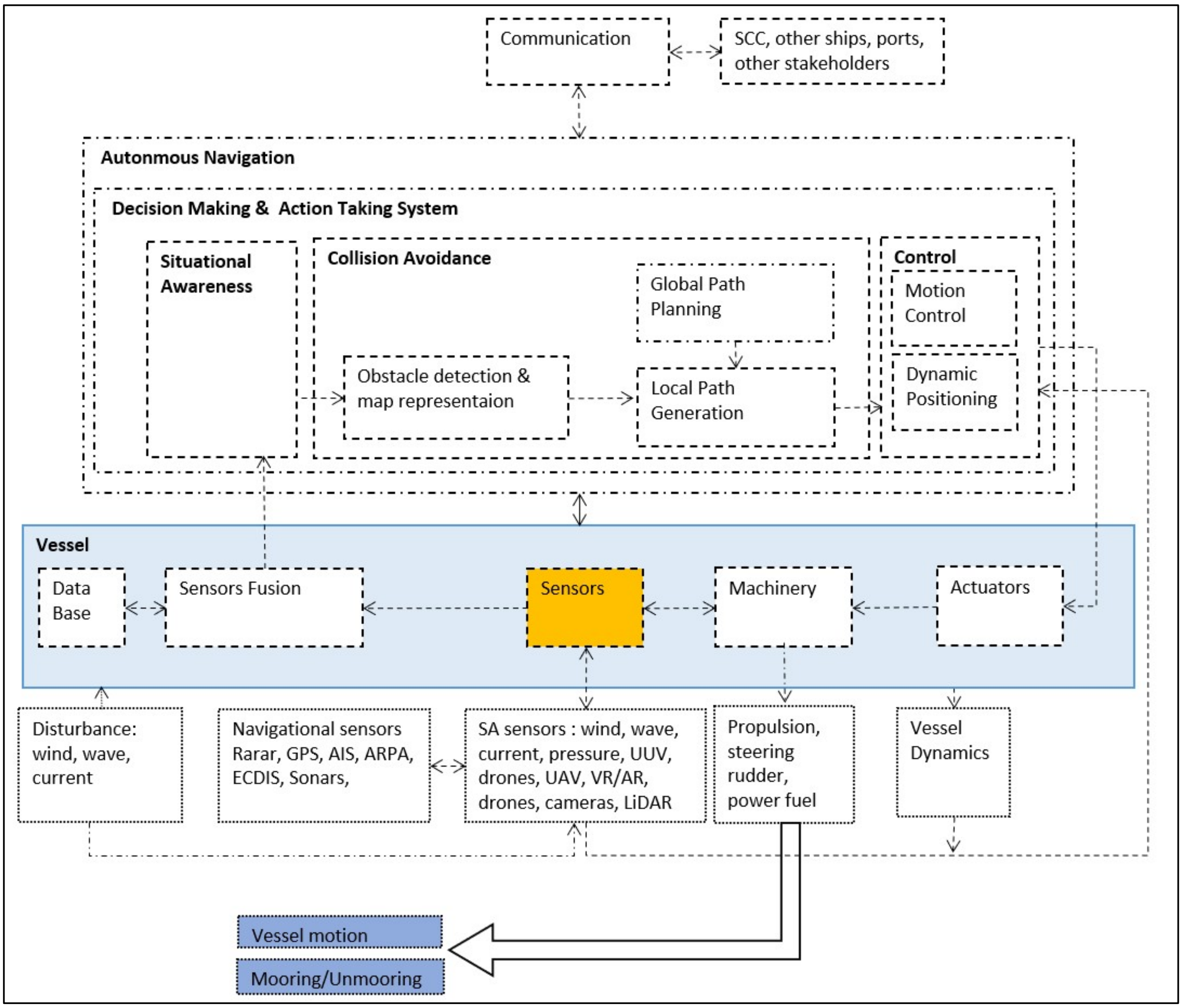

Figure 1. Autonomous navigation architecture.

3.2. Decision-Making and Action-Taking System

The virtual captain onboard MASS requires localised decision-making modules; thus, there are various agent-based systems with distributed intelligence strategies throughout the vessel [51]. Decision-making and action-taking are in charge of defining the overall trip (from origin to destination), considering long-term data, ship real-time data, and sharing information from cooperative vessels [56,63]. Typically, the system involves navigation, guidance, control, collision avoidance and motion planning [4,56].

This system is the brain for autonomous navigation and includes all the subsystems of autonomous navigation. It is a computer with different software that obtains data from situational awareness and collision avoidance subsystem sensors. Then, it calculates the desired output that adapts to the best solution of algorithms [63]. After this, the output is sent to motion control and path following or another module to keep the ship on a safe track and maintain course and speed. The latter mainly counts on the actuators (e.g., steering pumps, fuel valves, fire extinguishing systems, etc.) that control all shipboard processes without the need for human intervention, see the process in Figure 1.

The decisions are made up and carried out based on artificial intelligence decision algorithms. Artificial intelligence (AI) forms the core of decision-making capability to navigate MASS [65]. Artificial intelligence, i.e., machine learning and deep learning algorithms, is an intelligent process created by machines where the computer is perceptive and thinks and solves a problem on its own [66]. Machine learning is one of the most evolving procedures that solves problems relating to the data by involving an algorithm that appraises and separates data and develops logic [61]. Machine learning algorithms are capable of undertaking intelligent decisions, but because it becomes complex when dealing with unstructured data, deep learning can solve this challenge. Deep learning is a subset of machine learning that utilises a hierarchical level of artificial neural networks to perform machine learning in that the artificial deep neural networks (deep learning-based framework) act as a human brain with a web of connected neuron nodes [61]. The deep learning methods, for example, mimic helmsman behaviour, thereby being seen as a major and promising method in developing autonomous ships. Thus, more advanced control algorithms with more robustness and reliability are now under development in the marine sector [67]. AI and ML play a pivotal role in the autonomous functioning of MASS by enabling real-time decision-making and reducing the need for human intervention. Through machine and deep learning algorithms, these technologies process vast amounts of data from sensors to ensure safe and efficient navigation while continuously monitoring conditions to adapt to changes in the environment. AI systems are integrated with other technologies, such as sensors for situational awareness and communication networks for remote operation, to create a fully autonomous decision-making system that supports the vessel's operations.

3.3. The Situational Awareness (SA)

Situational awareness (SA) is crucial for conventional shipping operations and specifically for MASS. SA is seen as a sensory instrument to identify, monitor, and forecast (status in the near future in a specific volume of space and time) threats and objects including their specific characteristics and parameters. Thus, this enables other subsystems to deal with such issues instantly, while ships can detect obstacles and avoid collision efficiently [68,69].

MASS operation is based on data and information from various sensors and equipment about surroundings and the internal ship systems. While considering that lookout duties in MASS might be removed, SA requires additional and redundant sensors compared to conventional ships to ensure reliable and safe navigation [70]. An advanced sensor module conducts the lookout duties onboard MASS [71]. Sensors provide the means for the autonomous platform to perceive its environment [56], and SA sensors' data support onboard crew, VC, and Remote Control Centres (RCCs). Sensors provide vessel state information (e.g., position, speed and heading), environmental information (e.g., wind speed and direction, current velocity, and wave), and information about other ships (e.g., speed, heading, type, etc.) in this sense, studies reviewed the sensors for automobile [72] and maritime applications [56]. The advanced sensor module supports the e-navigation solution onboard manned conventional ships, which helps navigators and reduces the information overload and conflicting information from various sensors, thereby providing only what is needed to be performed (decision support systems) in accordance with COLREGs [71]. Notably, sensor instruments used in SA technologies can be subject to errors such as drift, noise, and calibration inaccuracies, which may affect data reliability. These errors can impact the system's ability to make accurate real-time decisions, highlighting the need for robust error mitigation strategies. The SA technologies, see Figure 2 below, are explained in the following subsections.

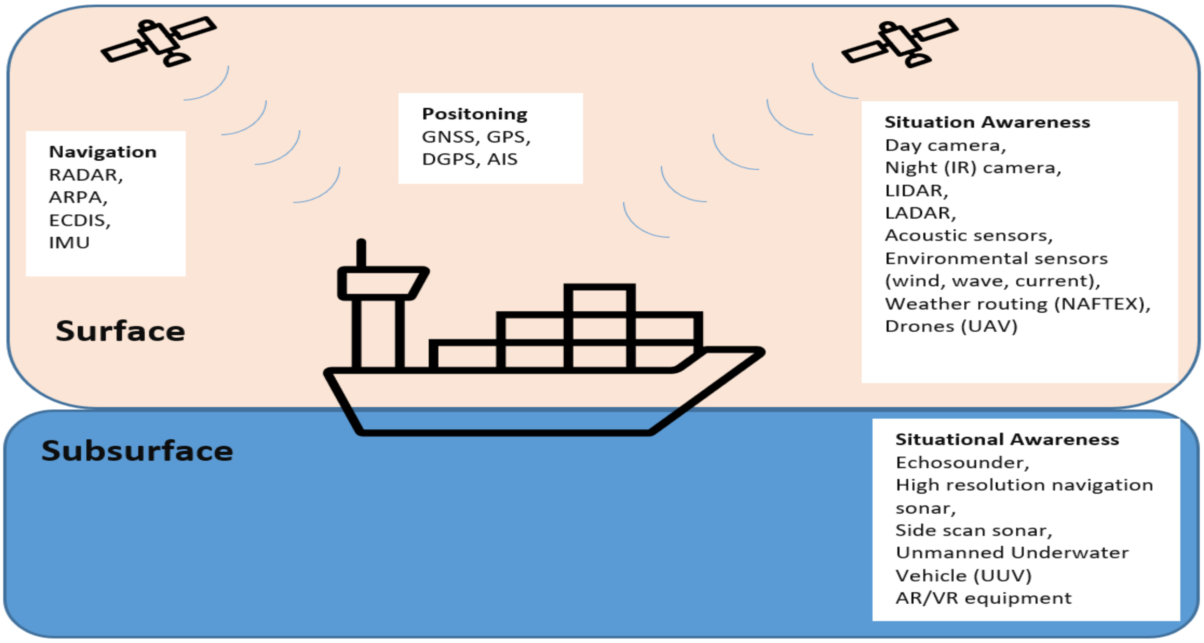

Figure 2. MASS situational awareness technologies.

3.3.1. Navigational Technologies (Sensors)

There exist commonly used sensors onboard conventional ships, which retrieve and provide data from the surrounding environment and from the ship itself for safe navigation [63]. These sensors are still required for MASS. The Autoship project suggested that MASS sensors can be as well placed onshore for cost efficiency, which can feed many MASSs and RCCs using robust communication links [73]. Key technologies include the **Global Navigation Satellite System (GNSS)**, which provides precise geo-spatial positioning through systems like GPS and DGPS, with the latter offering accuracy within 1–10 m [4,74]. The **Inertial Measurement Unit (IMU)** tracks vessel motion, aiding stability and collision avoidance [75–78]. **Radar** detects objects and provides range data, with long-range radars (S/X-bands) suited for open waters and short-range radars (KA/W-bands) optimised for harbours [56]. The **Automatic Identification System (AIS)** facilitates ship-to-ship and ship-to-shore communication, providing critical navigation and voyage data [55,56,74,79]. **Automatic Radar Plotting Aid (ARPA)** enhances obstacle detection and computes COLREGs-compliant manoeuvres, working in tandem with AIS to identify potential risks [4,55,74]. Finally, the **Electronic Chart Display and Information System (ECDIS)** integrates data from multiple sensors into real-time navigational charts, improving situational awareness and safety [74,77]. While these technologies form the backbone of MASS navigation, additional advancements are essential to ensure situational awareness on par with human operators [50].

3.3.2. Situational Awareness Technologies

Day and Night Vision Cameras

Day and night vision cameras are essential for MASS and thus should enable continuous vision 360° around the ship in four dimensions (x, y, z, time), in daylight and dark, and in different weather conditions including heavy rain, snow and fog, at an accurate and higher resolution than what a human could obtain [65]. The **day vision** cameras provide colour information about surroundings (ships, obstacles and aids to navigations (ATONs)) with high resolution, which can be further interpreted by analytical algorithms to identify and determine objects' characteristics and locations through the use of GNSS and ECDIS, among others [65,80].

Such technology, **day vision cameras,** produces massive data for analysis and transmission; however, it cannot be used in dark environments or bad weather (e.g., fog, rain) [56]. Therefore, infrared (IR) and thermal cameras are best suited for night vision (dark), such as the Long-Wave IR (LIWR) cameras that passively receive objects' radiation (8–14 µm) IR wavelength (i.e., sensitive). The Microbolometer-based LWIR camera, which is not a high resolution, can be used and does not require cooling. Additionally, the Short-Wave IR (SWIR) camera technology can be particularly used for short-range detection in humid and foggy weather, but it comes with low spatial resolution [27,52,72]. Closed-circuit television (CCTV) can be used to further improve vision [81]. Although the combination of two monocular cameras can be used to produce stereo imaging (3D map), it is still complex to analyse thousands of images and match them by control algorithms; therefore, a combination of LIDAR and Radar data are used, in addition to the fusion of such data, therefore providing robust full pictures and detailed maps of surroundings [27,56].

LIDAR and LADAR

Light Detection And Ranging (LIDAR) and Laser Detection And Ranging (LADAR) are scanning sensor technology using IR laser beams for accurate distance measurement [56]. LIDAR gives 3D pictures, semantic and spatial, and the objects can be identified based on artificial neural networks [82].

The LIDARs are not marine robust so far; thus, further adaptation in maritime applications is required [52]. In addition, LIDAR is based on rapidly moving mechanical elements and functions in line of sight; hence, it is influenced by harsh weather and poor visibility (fog, rain and snow), same as IR cameras [47,56]. Therefore, complementary sensors such as sonar, cameras, and radar are still needed, for example, LIDAR data can be complemented by fused data from video imagery to detect new variances.

Sound Detection Sensors

Sound signals (acoustic) are an essential technology in ship navigation. The roles of ship signals are explained in COLREGs. Sound signal technologies are needed for MASS, especially with the reduction of crew or elimination of lookouts, e.g., **microphones** [50,77]. These sensors pick up such sound signals (horns, whistles, bells, gongs, and guns) in fog, distress signals, or regular sound such as those of the aids to navigation (ATONs), and in the environment such as sound signals of waves crashing on rocks [65,82]. Other ships may give away horns and whistles, showing their intentions for short-range traffic. Sound sensors analyse and process signals, giving information on the source type and bearing, and dependent on its strength, may give a range. There exist algorithms for MASS, applicable for audio signal detection, classification, and localisation [82]. Such information can be fused with other sensors for broad SA. For example, in fusion with video imagery, cameras, RADARs, and LIDAR, the direction-of-arrival (DOA) of the target sound signal can be defined in addition to the approximate target location in live video [72]. The incorporation of sound sensors makes MASS compliant with COLLREG regulations [82].

Weather Sensors

The weather conditions in the water and atmosphere affect (manipulate) every side of the ship's navigation, thereby influencing ship safety (capsizing or sinking), particularly when carrying out evasive manoeuvres in collision avoidance [55]. In MASS, required global and local weather information can be obtained from weather centres through **Navtex,** which is part of the GMDSS (Global Maritime Distress and Safety System). The information supports weather routing by recommending routes prior to and during each voyage, considering several navigational constraints and global weather forecasts [51]. Additionally, basic weather sensors can be integrated onboard MASS to provide real-time data on wind (e.g., anemometer) and wave speed and direction, current, temperature, barometric pressure, humidity and sea temperature, which can be utilised to compensate for the effects of wind, currents and other phenomena throughout the voyage [65]. Various autonomous collision avoidance, path planning, and energy efficiency algorithms consider data from atmospheric, water, and weather monitoring instruments.

Underwater (Subsea) Sensors

Various ultrasonic sensors are needed for depth sensing **(subsea),** enabling constant vigilance of water depth below the keel, such as the echosounder, high-resolution navigation sonar, side scan sonar, Unmanned Underwater Vehicle (UUV) [65,77,83]. These sensors are necessary for underwater visibility ahead and around MASS, providing terrain tracking capabilities and high-resolution bathymetry and imaging of seabed, which help in detection and response to uncharted threats and thus avoid groundings and collisions [65]. The use (UUV) MASS extends vision below the waterline, ahead of and in the local vicinity [65].

Virtual Reality (VR) and Augmented Reality (AR) Equipment

AR and VR equipment, e.g., headsets, tablets, interactive flat screen displays, and cave and curved wall displays, can be used in the bridge by watch officers, enabling 3D immersive display [47,65]. For example, the captain and watch officers can use the giant screen display (VR/AR), which overlays the surrounding environment of the ship with an augmented reality view supported by artificial intelligence tools that spot and label all the moving and static objects around the ship [65]. In the case of fully autonomous MASS, these technologies are used by RCC operators.

Drones

Drones, such as compact and vertical take-off unmanned aerial vehicles (UAVs), can be used for environmental scanning as another approach to widen situational awareness [84]. Drones carry out scouting surveys in front of MASS using an array of different sensors [85]. Drones not only help in navigation but also detect security threats early.

E-Navigation

Another common expression in maritime digital communications is E-Navigation, which is used as an approach to enhance the safety of navigation and operations of commercial shipping. E-navigation solutions are intended for SOLAS-based ships (International Convention for the Safety of Life at Sea). The International Maritime Organisation (IMO) defines E-navigation as "the harmonised collection, integration, exchange, presentation and analysis of marine information on board and ashore by electronic means to enhance berth to berth navigation and related services for safety and security at sea and protection of the marine environment" [86]. E-navigation minimises navigational errors, incidents and accidents through the transmission and display of positional and navigational information in electronic formats, i.e., the IHO S-100 as the common Data Standard for information exchange and its variants S-101 ENC, S-102, S-103, etc. The IMO E-navigation Strategy Implementation Plan (SIP) was approved in 2014, which includes S1. Improved, harmonised and user-friendly bridge design; S2. Means for standardised and automated reporting; S3. Improved reliability, resilience and integrity of bridge equipment and navigation information; S4. Integration and presentation of available information in graphical displays received via communication equipment; and S5. Improved Communication of VTS Service Portfolio.

It is worth noting that the IMO established E-navigation with the intention of reducing human and traditional machine errors and improving safety related to navigation, that is, to better protect passengers, crew, maritime systems and the environment [87]. The E-navigation organises data on ships and onshore and seamlessly enables data exchange and communication between ships and the ship and shore [88]. Real-time data and information are exchanged, such as weather, ice charts, the status of aids to navigation, water level and rapid changes in port status, voyage information, passenger manifest, and pre-arrival report [89]. This definitely assists the shipping industry in improving safety via accurate decision-making that minimises errors and makes operations reliable.

E-navigation stimulated the growth of fully autonomous MASS projects in the last decade [90]. The proposed digital high and very high-frequency radios as a communication system, e.g., VHF Data Exchange System (VDES), will intertwine with e-navigation and the S-100 messages [53]. Services of E-Navigation, e.g., route exchange, make ship intentions more transparent, particularly in traffic separation schemes, thus, this facilitates future encounters between manned ships and autonomous ships [91].

3.3.3. Effectiveness of the Technologies

SA technologies are widely used across various autonomous systems, with evidence from both industry and research supporting their effectiveness. For instance, LIDAR and cameras provide high-resolution environmental mapping, proven to enhance object detection and tracking in both day and night operations. Weather sensors offer quantitative insights into environmental conditions, which is critical for decision-making, while sound detection sensors contribute to early threat identification, enhancing navigational safety. Studies in autonomous navigation systems have shown that these technologies, when integrated effectively, significantly improve situational awareness by providing reliable, real-time data across various operational conditions. Although comprehensive quantitative analysis specific to Maritime Autonomous Surface Ships (MASS) is limited, the performance metrics observed in other autonomous applications support the applicability and potential effectiveness of these SA technologies for MASS.

3.4. Sensor Fusion Technology

Although it is still necessary for conventional ships, the sensor fusion technology **(data processing technology)** is the topmost important technology in the transition of MASS to a higher level of autonomy. Considering that no single sensor technology can deliver adequate information about different conditions, the input from multiple sensors can be combined and analysed by the sensor fusion technology. Sensor fusion integrates inputs from, for example, radar, LIDAR, sonar, GPS, and cameras, allowing the system to achieve a reliable level of SA crucial for autonomous navigation. This approach mitigates the limitations of individual sensors by merging their outputs and enhancing the accuracy of object detection, tracking, and environmental mapping.

Sensor fusion is important because it increases data robustness and reliability, broadens the sensing capability, and collects maximum information on surroundings [72]. The sensor fusion system receives data and information from various sensors, i.e., the previously explained navigational and situational awareness technologies. The technology extracts and classifies features in the obtained data, thereby balancing sensors' strengths and weaknesses [72]. When data are processed, all inputs are considered, and attempts are made to average redundant and conflicting data with their inherent errors to produce a best-perceived truth of the surrounding environment [56]. This is achieved using artificial intelligence algorithms for complex analysis, processing and image segmentation, e.g., deep neural networks [82]. Different ways for sensor fusion and data processing concepts are suggested, such as image segmentation and redundant data reduction [27].

The fused data can be mapped and processed to extract relevant information (e.g., ship state, environment, surroundings, etc.) and passed to situational awareness and collision avoidance subsystems (Figure 1). Thus, the fusion technology maintains an updated detailed map, and, as such, optimal situational awareness is guaranteed in all conditions and situations enabling safe navigation and collision avoidance. Further, sensor fusion decreases massive data and information gathered, which reduces the load of data transferred externally to the RCC, for example. This sustains efficient ship communication [27,72].

3.5. Database

Thousands of sensors onboard the ship generate small and large sophisticated data formats, which need to be stored in the internal ship database. An internal database is very important for decision-making and action-taking systems onboard MASS or in RCC [81]. The data in the database can be retrieved anytime by sensor fusion technology. On the other hand, the data stored enhances data engineering techniques (AI algorithms). The data engineering converts the raw data into the desired format required for the processing, enables data analytics, and generates the working models, which are used for path optimisation and energy efficiency, among others [61]. The data collected could feed the so-called Big Data platforms.

Similar to the database concept, the **Voyage Data Recorders** (VDR) is also used in many ships. VDR is an electronic system that records all positional, navigational and sensor information during a voyage (e.g., RADAR, ECDIS, GPS audio-visual data) [77]. VDR consists of a data aggregating unit and a storage unit, and if the ship is involved in collisions, the VDR is consequently used by competent authorities for further investigation.

3.6. Collision Avoidance (CA) Subsystem

It is not enough that ships sail from origin to destination, how to sail and safely the ship manoeuvres to avoid collisions, grounding and stranding is a critical problem. An autonomous collision avoidance system is a key to MASS's full autonomy, including its being as a decision support system for the crew onboard [85]. Via the collision avoidance subsystem, various solutions are used to plan the voyage, compute a global path to avoid impediments, and detect and avoid all kinds of obstacles, i.e., dynamic (e.g., fishing vessel, cargo vessel, pleasure yacht, small speed boats), or static (e.g., terrain feature, bank/shallow, offshore structure, rocks) [47,63]. Close-range collision avoidance systems were frequently reviewed [4,19,56].

Collision avoidance (CA) is responsible for safe navigation by assessing the risk of collision with static and moving obstacles (ships), either at open sea or harbour and thus navigating the ship to avoid such collision by providing the desired course and speed [4]. Collision avoidance by humans is subjective, thus errors may happen [61]. Generally, it is estimated that human error contributes to 89– 96% of maritime collisions [4], whereas 56% of collisions are due to violation of the Convention on the International Regulations for Preventing Collisions at Sea (**COLREGs**)[1] [92]. The IMO established **COLREGs**-1972 regulations, as guidelines procedures to avoid collisions and ensure safety for encountering vessels at sea. COLREG scenarios such as crossing, head-on and overtaking, and potential manoeuvres to avoid a collision are customarily applied by vessel crew; however, through autonomous navigation, the system does that, and it has the potential to minimise errors to zero [4,52]. While COLREGs were made for manned ships, their key elements should be applicable by MASS CA subsystems, either manned or not [57,85]. Designing an autonomous CA respecting COLREGs Part B was simulated in various studies, e.g., [4,56,93].

Various ways were suggested to simplify interactions between MASS and conventional ships, which include modifications in collision regulations (COLERGS), e-navigation and traffic separation schemes [91].

The autonomous CA decides what actions the vessel takes dependent on artificial intelligence algorithms (machine learning and deep learning) that provide the right decisions in light of information and data collected from the SA subsystems. Algorithms maintain the real-time reaction (CA) capability while eliminating the non-linearity (computation complexity) introduced by extreme endogenous and exogenous ship dynamics (navigation influencing factors) [55]. The decisions made by the CA (algorithms) account for the environmental effects such as wind and ocean currents, waterways traffic density, ship dynamics and manoeuvrability [88].

Autonomous CA consists of mainly two subsystems, i.e., obstacle detection and map representation, and path planning (Figure 1). The path planning is either global path planning or local path generation (reactive control) [4,52,71]. The CA system (computers) carries out path planning and generates signals (commands) that feed the control subsystem (motion and path following), which controls the motion actuators and hence maintains the required course and speed to avoid collisions.

3.6.1. The Obstacle Detection and Map Representation

To avoid obstacles, an accurate representation of the environment is required, a full external maritime picture [4,57]. The obstacle detection and map representation must be defined in advance before performing the collision avoidance manoeuvres [57]. **The map representation** is an essential part of the reactive path planning CA and is used to make behavioural decisions [56,63]. A map of the current environment of the outer world (Two-Dimensional (2D)/Three-Dimensional (3D) model) is maintained and represented. This subsystem detects and integrates obstacles (e.g., harbours, ports, islands, and buoys, which can be retrieved from nautical and terrain charts), including shipping lanes, coastal terrains, and shoals [57]. Similarly, the dynamic obstacles (other vessels) are represented, classified and tracked utilising SA sensors information, e.g., AIS, ARPA, ECDIS and other sensors [1,4,52,62]. The retrieved obstacles' classification, speed, and kinematic properties are used to estimate their future position. Object recognition, identification and classification are achieved through algorithms (deep learning methods, e.g., convolutional neural network) for imagery, which improve Automatic Target Recognition (ATR) and Maritime Domain Awareness (MDA) [61]. See various obstacle detection tools and purposes in Table 2, noting that smart sensors (radar and vision) provide precise obstacle detection for USVs but may be affected by environmental conditions. Stereo obstacle detection accounts for pitch and roll but adds complexity. Integrated algorithms (Voronoi, visibility, Dijkstra) offer thorough mapping but need high processing power.

Table 2. Obstacle detection tools.

Tool name/Algorithm	Application	Purpose	Study
Smart sensors (radar and vision technologies)	USV	Obstacle detection for high-speed USV	[94]
Stereo obstacle detection algorithm	USV	Integration of boat's pitch and roll	[78]
Integrated algorithm based on Voronoi diagram, Visibility algorithm and Dijkstra search algorithm	USV	Obstacle detection and map representation	[95,96]

USV: unmanned surface ship.

The common approaches to represent maps are qualitative (topological maps), which describe the spatial locations without numerical references (suitable for global path planning), and quantitative (metric maps), which describe geometric representation based on waypoints (suitable for local path planning). The geometric information of metric maps is necessary to plan and execute the trajectory while avoiding collision by the utilisation of optimisation algorithms for the optimum route. The popular metric maps are explained in [4], e.g., meadow map, Voronoi diagrams, regular occupancy grid, and quadtree mapping [95,96]. Additionally, hybrid map representation methods to reduce data and fuzzy modelling methods for dynamic environments and weak sensor precision have recently been adopted [78,94].

3.6.2. The Path Planning

Path planning (Figure 1) is a software system divided into global (deliberate) and local (reactive) path planning or a hybrid of the two [52,57,62,97]. Path planning accounts for the statics and dynamic obstacles and dynamics of the specific vessel [4]. The path planning technique replicates the real environment, utilising modern artificial intelligence techniques such as machine learning and deep learning methods [61]. For example, path planning for inland waterway autonomous vessels uses A*BG algorithms, which depict the navigational system of autonomous ships [62]. In different studies, the COLREG manoeuvres were integrated into global, local or hybrid path planning techniques where additional constraints are put upon the generated paths to conform to the regulation.

The Global Path Planning

Global path planning is based on prior information, in other words, a geometrical trajectory is made to avoid known obstacles from the mission origin to the destination. Retrieved from the electronic chart, waypoints, and headings, in addition to factoring the speed determined, path planning sets the whole voyage track to avoid static obstacles (islands, shallow waters, buoys, etc.) [4,57]. The system has a lot of drawbacks, i.e., tasks are carried out offline before the voyage starts, in addition to large computational memory costs and unwanted sharp turns [4,62,63]. Global path planning is not sufficient as collision with a dynamic obstacle may happen because its computationally intensive algorithms are not designed to run in real-time.

Soft computing techniques, mathematical models, and linear programming algorithms that simulate the ship dynamics are used to optimise the path. Algorithms can be utilised to quickly find optimal paths, such as the following, derived from [4,19,27,52,55,64], that are used in different studies:

i. Evolutionary algorithms (e.g., Genetic Algorithms (GA), strongly typed genetic programming (GP), Ant Colony Optimisation (ACO), Particle Swarm Optimisation (PSO);
ii. Graph-based Heuristic Search Algorithms (e.g., A* and its extensions);
iii. Hybrid of evolutionary and heuristics (e.g., Genetic Algorithm-Manufactured Manoeuvring, and Hierarchical Path-Finding A* Algorithm);
iv. Sampling-based methods (e.g., probabilistic roadmap PRM, and the rapidly exploring random tree RRT).

The following Table 3 presents the popular tools used for global path planning, their applications and their purpose. It is worth noting that evolutionary algorithms, neural networks, and fuzzy logic aid ASV collision avoidance, though complex. For USVs, the Multi-layered Fast Marching method and Fast Marching Square algorithm optimise paths and counter environmental impacts. GPU-based algorithms, A*, and Ant Colony Optimisation enhance trajectory planning under uncertainty, while EEA* focuses on energy-efficient paths.

Table 3. Global path planning tools.

Tool name/Algorithm	Application *	Purpose	Study
Evolutionary algorithms, fuzzy logic, expert systems, and neural networks	ASV	Collision avoidance	[55]
Multi-layered fast marching (MFM) method	USV	Minimise the negative effects of environmental influences (currents, wind)	[98]
Fast Marching Square algorithm	USV	Optimal trajectory and collision avoidance	[99]
Rule-based Repairing A*, Finite Angle A*, and Smoothing A* algorithms	ASV, USV	Optimal path	[4,100–103]
Ant Colony Optimisation (ACO)	USV	Trajectory planning	[104–106]
Genetic algorithms	USV	Optimal path under environmental loads	[107]
GPU based algorithms	USV	State transition model for trajectory planning under motion uncertainty	[108]
Experimental testing path manager	USV	Execution of survey operations	[109]
EEA* algorithm	Con	Energy efficient considering environmental effects	[110]

Con: conventional, MASS: maritime autonomous surface ships, ASV: autonomous surface ships, USV: unmanned surface ship.

The Local Path Planning

The local path planning is reactive and dependent on sensor information. While the ship is underway, it incorporates the reality of the environment based on repeated perception–action processes [4,19,27,55,111]. Accurate reactive path planning obtains information from sensors fusion system (if installed) or accumulates information from various SA sensors about static (islands, coast, rigs) and moving obstacles (e.g., vessels, boats), own vessel state (heading, speed, location) environmental data (e.g., wave, wind, sea currents), and constraints (kinematic and dynamic)[2] [4,55,111]. Local path planning utilises the Line of Site (LoS) method and algorithms such as Artificial Potential Fields (real-time path planning). These methods are memoryless and effective in real-time with low computational requirements, however, as a disadvantage, the system may become trapped in local minima instead of achieving objectives [52]. Further advances in algorithms overcome the local minima issues (e.g., Harmonic Potential Fields) [4,57]. Other reactive path planning algorithms have been developed over the years, such as the velocity obstacle methods [112] and dynamic window (DW) algorithms, which can include dynamic and kinematic constraints of the vessel [97,113,114]. As can be seen in Figure 1, the local path planning depends on the reception of the local map and current obstacle information (map representation and obstacle detection subsystem), so once collision is detected, these current maps are used as a base to create new waypoints and generate manoeuvring information (commands to be sent to the control subsystem). Table 4 presents the popular tools used for local path planning, its application and purpose. Several algorithms ensure USV and ASV compliance with COLREGs, such as Artificial Potential Fields (APF), model predictive control (MPC), and velocity obstacles (VO). Optimisation methods, including grey wolf optimisers and swarm optimisation, focus on energy-efficient path planning and trajectory optimisation. Advanced algorithms like deep reinforcement learning (DRL) and the observation–inference–prediction–decision (OIPD) model enhance real-time collision avoidance and compliance with maritime regulations.

Table 4. Local path planning tools.

Tool name/Algorithm	Application	Purpose	Study
Local normal distribution-based trajectory algorithm, grey wolf optimiser	USV	Path optimisation with minimal energy consumption	[115]
Artificial Potential Fields (APF)	USV	COLREGs compliance	[116]
Optimal reciprocal collision avoidance algorithm	USV	COLREGs compliance	[117]
Way-point guidance by line-of-sight coupled with a manual biasing scheme algorithm	USV	COLREGs compliance	[92]
Probabilistic timed automata (PTAs) algorithm	USV	COLREGs compliance	[118]
A Multiobjective Optimisation Approach algorithm	USV	COLREGs compliance	[119]
Model-referenced trajectory planner	USV	COLREGs compliance	[120]
A Balance-Artificial Potential Field Method in confined areas	USV	Obstacle avoidance	[121]
Artificial Potential Field algorithms	USV	Collision avoidance and COLREGs compliance	[116]
Multi-objective swarm optimisation	USV	Trajectory planning	[119,122]
Angular rate-constrained Theta * algorithm	USV	Real time collision avoidance considering both angular rate (yaw rate) and heading angle	[123]
Line-of-sight (LOS) guidance and velocity obstacle (VO) algorithms	USV	COLREGs compliance (rule 13 to 17)	[124]
Hierarchical multi-objective particle swarm optimisation (H-MOPSO) algorithm (evolutionary)	ASV	COLREGs compliance	[125]
Improved time-varying collision risk (TCR) measure	MASS	Collision avoidance that reflects the dangerous level of the approaching ships and the difficulty of avoiding collisions	[126]
Model predictive control (MPC) method	ASV	COLREGs compliance based on AIS information	[127]
Velocity obstacles (VO) method	USV	COLREGs compliance	[112]
Field theory including the virtual spatial electric field and velocity field	USV	Optimal collision avoidance strategy considering the energy and other loss	[128]
Modified Artificial Potential Field (APF)	USV	COLREGs compliance	[129]
Path-Guided Hybrid Artificial Potential Field (PGHAPF) method	ASV	COLREGs compliance	[130]
Novel general obstacle avoidance algorithm LROABRA	USV	Obstacle avoidance approach for high-speed USVs	[131]
Observation–inference–prediction–decision (OIPD) model	ASV	COLREGs compliance	[132]
Improved deep reinforcement learning (DRL) algorithms	MASS	COLREGs compliance	[133]
Recommended various quantification of qualitative COLREGS.	MASS	COLREGs compliance	[134]

MASS: maritime autonomous surface ships, ASV: autonomous surface ships, USV: unmanned surface ship.

Hybrid Path Planning

Hybrid path planning is a combination between the global and local path planning approaches [19,52]. A combination of online and offline algorithms can be maintained, i.e., possible optimal paths are calculated, but if the system faces dynamic obstacles, online ones are activated [27,55]. By doing so, the system increases the effectiveness of path planning and safety. Hybrid planning uses local path planning to deviate from the pre-defined waypoints, heading and speed to optimal paths (new heading and speed taking into account constraints) but still uses the information from global path planning to reach destination [52,57]. The following Table 5 presents the popular tools used for hybrid path planning, including their application and purpose. These algorithms enhance USV and ASV navigation by optimising path planning, ensuring COLREGs compliance, and enabling coordinated fleet control. However, heuristic and A* algorithms can be computationally demanding, potentially slowing down real-time responses. Neural networks and evolutionary methods require extensive training data and resources, and multi-layered approaches may struggle with rapidly changing environments. Balancing their precision and efficiency is crucial for effective deployment in maritime settings.

Table 5. Hybrid path planning tools.

Tool Name/Algorithm	Application *	Purpose	Study
Heuristic Rule-based Repairing A* (R-RA*) algorithm	USV	COLREGs compliance	[135]
Fast Marching Square algorithm	USV	COLREGs compliance	[136]
Heuristic search algorithm based on Bandler and Kohout's fuzzy relational products	USV	COLREGs compliance and optimal path	[137]
Avoidance algorithms for the C-enduro USV	USV	COLREGs compliance and optimal path	[138]
Hybrid dynamic window (HDW) algorithm	ASV	Trajectory planning	[97]
Evolutionary neural network algorithms	ASV	Anti-collision	[139]
A* graph-search algorithm and GODZILA (Game-Theoretic Optimal Deformable Zone with Inertia and Local Approach)	ASV	Obstacle avoidance	[101]
Hybrid dynamic window (HDW) algorithm	ASV	Trajectory planning	[97]
Evolutionary neural network algorithms	ASV	Anti-collision	[139]
A* graph-search algorithm and GODZILA (Game-Theoretic Optimal Deformable Zone with Inertia and Local Approach)	ASV	Obstacle avoidance	[101]
Fusion algorithm	USV	Obstacle avoidance	[140]
Fast marching (FM) method	USV	Deploy multiple USVs as a formation fleet	[141]
Neural networks (NNs) backstepping and the minimal learning parameter (MLP) algorithms	ASV	Leader–follower cooperative formation control	[142]
Time-varying tan-type barrier Lyapunov functions (BLFs)	ASV	LOS range and angle constraints for group ASV leader–follower formation control	[143]
Network-based incremental predictive control scheme	USV	Networked USV formation systems under a leader–follower structure	[144]
Second order formation dynamic model, multi-layer neural network and adaptive robust techniques	ASV	Formation controller for a number of surface vessels	[145]
Off-line and on-line optimisation methods	USV	Use of a team of USVs for the security of civilian harbours	[146]
Heuristic research algorithms (A*, A*ABG)	ASV	COLREGs compliance	[62]
A* heuristic search algorithm for	ASV	Real-time path planning, incorporating COLREGs	[4]
Fast Marching Square and velocity obstacles methods	MASS	Find an optimal path considering the collision risk and proximity from the obstacles	[147]
Heuristic approach and deterministic method algorithms	Con	Collision avoidance through autonomous navigation	[64]
DTW algorithm, least square support vector machine method	Con	Autonomous path following	[148]

Con: conventional, MASS: maritime autonomous surface ships, ASV: autonomous surface ships, USV: unmanned surface ship.

Cooperative Path Planning and Platooning

Cooperative behaviour between vessels of the same and different types is suggested to improve group CA response [4], which enables multiple MASSs to navigate in formations to arrive at a destination or do a certain mission. In addition, MASS cooperative operation yields efficient operations and greatly improves fault tolerance and adaptability [149]. From cooperative COLREGs response perspectives, ships can follow formation control, swarm, or platooning, i.e., fleet path planning and fleet formation control. A fleet of vessels can navigate together toward a destination and avoid obstacles together in popular geometric formation patterns (e.g., Line, column, diamond and wedge) [4,56].

On the other hand, another MASS application is suggested where vessels can sail in **platooning** (**train concept)** [58]. Multiple MASSs, thus, follow a conventional leader vessel, and the vessel can establish wireless communication links, such as the concept in the NOVIMAR project. The platooning can be applied within hub and feeder ports, i.e., small feeder services [58].

3.7. Motion Control and Path Following

Motion control planning (Figure 1) encompasses trajectory tracking, path following, manoeuvring, steering, and heading controls [4,150]. It is more complex because it physically activates mechanical components [63]. In addition, the trajectory tracking and path following are quite complex due to the strong non-linearity and uncertainties in environmental conditions [151]. The motion control system keeps and monitors **the trajectory** generated in path planning (i.e., path following) [63]. The autopilot performs an essential role in controlling the heading with respect to time and surrounding obstacles, such as other ships [62,63]. Various motion control approaches have been reviewed in [4].

Many techniques of automatic steering are available, which mimic a helmsman and account for ship dynamics (via deep learning frameworks) [51], linearity and non-linearity effects (rolling, pitching, yawing, etc.), and environmental impact (wave, current, wind) [4,52]. The intelligent control techniques and methods are mature and adopted, e.g., adaptive fuzzy autopilot, Artificial Neural Networks (ANNs), Neurofuzzy methods, iterative Lyapunov-based technique, model predictive control (MPC) and the optimal theory methods [4,52,56,64,151–156]. Table 6 presents the popular tools used for motion control and path following, their applications and their purpose. These algorithms significantly enhance USV and ASV navigation by improving compliance with COLREGs, optimising trajectory planning, and enhancing stability under disturbances. For example, model predictive control (MPC) and adaptive controllers handle dynamic conditions effectively, while neural networks and genetic algorithms optimise control precision. However, many of these methods, such as convolutional neural networks and sliding mode controllers, require substantial computational resources and may struggle in complex or variable environments. Balancing computational demand and real-time responsiveness is crucial for effective use, especially in scenarios requiring high-speed or adaptive responses.

Importantly, it is worth noting that advanced guidance systems are indispensable for ensuring accurate motion control and path following of MASS including the USVs and ASVs. Technologies such as *Line of Sight (LOS)* guidance put the ship on the targeted trajectories by calculating the right heading angle, taking into account the ship's dynamics and surrounding environment environmental disturbances such as currents and wind. *Vector Field Guidance*, on the other hand, creates mathematical vector fields for robust navigation in dynamic environments, advancing the ship's ability in obstacle avoidance and accurate dockage [148]. Furthermore, the *Artificial Potential Fields* are utilised for collision avoidance via the generation of virtual forces [130]. *Dynamic programming-based path planning* augments navigation by providing decision support that improves energy efficiency and time, whereas hazards are being avoided [107]. Lastly, *algorithms such as Fast Marching* deliver real-time pathfinding solutions, predominantly useful in dynamic obstacle scenarios [107].

Table 6. Motion control and path following tools.

Tool Name/Algorithm	Application *	Purpose	Study
A deep convolutional neural network (Alexnet) algorithm	USV	COLREGs compliance	[155]
Angle guidance fast marching square method	USV	Autopilot module	[157]
Trajectory Unit Method	USV	Motion control for in a small range of scenarios	[158]
Model predictive control (MPC) approach based on adaptive line-of-sight (LOS)	ASV	Track reference paths with various disturbances	[159]
Backstepping adaptive sliding mode controller was	USV	Stabilisation problem of the trajectory tracking error equation	[160]
Jacobian Task Priority-based Approach	USV	Completion of a path following mission, and vehicle velocity regulation	[67]
Guidance motion control law	USV	Solve the guidance problem for under-actuated systems	[161]
Robust controller based on adaptive sliding mode control in combination with the radial basis function neural network (RBFNN)	ASV	Suppress the effect of parameter variations and external disturbances	[152]
Discrete-Time Sliding Mode Control (DTSMC)	USV	Straight line following and regulation of linear and angular speed	[162]
Genetic algorithms (GA), fuzzy logic controller (FLC)	USV	Optimise PID controllers (rudder angle)	[151]
Local control network (LCN) techniques, underway docking procedure	USV	A Local Control Network Autopilot	[163,164]
Neural network-based approaches	ASV	Manoeuvring, steering and course control	[153–156]
Angular velocity guidance algorithm	USV	Address the heading control problem caused by dynamic linearisation	[165]
Backstepping controller	USV	Minimise the effects of variable mass and drag	[166]
Nonlinear proportional derivative, backstepping and sliding mode feedback controllers	USV	station-keeping heading and position under wind and current disturbance	[167]
Line-of-sight guidance control laws	ASV	Leader–follower motion control of multiple ASV	[168]
Safety distance constrained A* approach	USV	Coordinated and cooperative navigation of USVs in a constrained maritime environment	[169]
Closed-loop controller by applying Lyapunov stability theory	ASV	Multiple USV automatic target tracking, obstacle and collision avoidance	[170]
Fisher information matrix (FIM)	ASV	Inter-vehicle collision avoidance and manoeuvring	[171]
Various algorithms for autonomous navigation	USV	Several different boats to perform significant missions both by themselves and in cooperative modes	[56]
Velocity Obstacle (VO) model using Dynamic Programming (DP) method	MASS	Optimal motion planning for MASS with presence of other conventional ships	[172]
Port-Controlled Hamiltonian (PCH), Lyapunov's direct method and backstepping approaches	USV	Track keeping with energy optimisation	[173]

MASS: maritime autonomous surface ships, ASV: autonomous surface ships, USV: unmanned surface ship.

Dynamic Positioning

Dynamic positioning (DP)[3] advances the motion control and path following subsystem, and it supports the highest level of MASS degree of autonomy (DoA 4—total autonomous ships). DP calculates where the ship can move, taking into consideration the ship's kinematic and dynamic constraints, and hence automatically enables the ship to hold its position or heading by using its propellers, rudders, and thrusters [27,43,73,174]. DP is linked to SA sensors, and it restricts areas of manoeuvre (waypoint boundaries). The AAWA suggested the integration of navigational systems for complete autonomous navigation, which consists of a **dynamic positioning system (DP)** connected with four interlinked modules, i.e., route planning (global path planning), situation awareness, collision avoidance (reactive local path planning), and ship state definition (virtual captain) [27]. **The ship state**

definition (SSD), or the virtual captain (VC), is the highest level in the ship and determines the current status of the ship, the operation mode as remote controlled or autonomous, in addition to the failsafe/fallback strategy. The VC activates the failsafe/fallback strategy when MASS experiences an unexpected reduction in connectivity simultaneously with an operational challenge, which would normally require RCC operator intervention. It includes the sequential steps: asking the operator to take manual control, if failed, slow down and proceed to the following waypoint, if failed, stop the vessel and stay in DP mode, if failed, navigate to the previous waypoint, if failed, navigate back to pre-set safe location [27].

3.8. Berthing and Unberthing

The MASS mooring and unmooring (docking and undocking) can be supported by the DP. However, autonomous or remote mooring is one of the essential challenges in ship control owing to many complexities, such as the non-linearity of the low-speed manoeuvring model, danger of collision, wind speed, wind direction, current, and ship dynamics [69]. Thus, until this issue is solved, MASS (DoA 3—remote-controlled ship that has no seafarers onboard and 4—fully autonomous) would require the presence of a crew to help in berthing. The MUNIN project described this crew as the onboard control team (OCT), who will embark during the port approach and departure to carry out normal ship crew duties [71]. Notably, port infrastructures need to be modified to facilitate mooring, e.g., through automatic mooring systems, remote control piloting, etc., [175]. The AAWA suggested that RCC operators may gain autonomous pilot licences [27].

4. Conclusions

Future ships will be highly digital and interconnected, integrating both onshore and offshore stakeholders, along with advanced software and hardware systems. It is clear that sustainable shipping is undergoing significant changes to incorporate automation and digitalisation, both of which require robust and comprehensive autonomous navigation systems. This study has provided valuable insights into the architecture of autonomous navigation systems. The review highlighted the technologies crucial for future shipping, particularly those relevant to MASS. The findings segmented the navigation system into key subsystems that allow autonomous vessels to make informed decisions, including situational awareness technologies, decision-making frameworks, and sensor fusion capabilities. Additionally, the architecture demonstrates how these systems integrate with onboard decision-making and external data inputs.

This study not only offers a comprehensive framework for autonomous navigation systems but also outlines how these technologies are applicable not just to MASS but also to conventional ships. The architecture presented here can serve as a consolidated resource for understanding the intricate components of autonomous navigation, positioning it as a valuable reference for both current and future maritime operations.

Technology, particularly SA sensors and sensor fusion, and decision support algorithms (artificial intelligence) for collision avoidance and path following make MASS a reality. However, the challenge is to amalgamate sensors reliably and cost-effectively. With regard to MASS, the autonomous navigation architecture built in this scenario achieves the four levels of autonomy, i.e., whether the ship is supervised by seafarers, remote controlled by RCC or fully autonomous. This study suggests that the technologies are mostly available and have been used in other automation sectors, e.g., aviation and land transport; however, they are not yet highly adopted in conventional ships, and with respect to MASS, few design projects and current large scale ship development adopted such technology, e.g., ReVolt [176], and YARA Birkeland [177]. This indicates the requirement for technology verification and adaptation in the maritime sector. Thus, the development will be a gradual and iterative process and will be subject to extensive testing and simulation. In the same fashion, standardisation (standardised digital interfaces) and interoperability[4] of technologies should not be neglected, as these factors are important for future technology uptake and keys to future MASS digital pipelines [47]. Some SA technologies were used in land transport (e.g., LiDAR, night vision cameras, etc.), however, using such technologies at sea would require them to be resilient to harsh weather and sea saltness. Notably, technologies, in general, are not only applicable to MASS but, by all means, applicable to conventional ships. Hence, their adoption highly assists seafarers in decision support systems and increases safety and efficiency during voyage navigation. For example, the use of situational awareness technologies and artificial intelligence technologies (machine learning and deep learning algorithms) minimises tedious calculations performed by seafarers.

This study identified different issues with respect to artificial intelligence (intelligent algorithms) in addition to future requirements:

i. **COLREG** compliance is clearly challenging for MASS. For proper actions and decisions, there is a need to integrate and quantify qualitative COLREG protocols to be able to code collision avoidance algorithms [91] (a challenge for programmers). Transcription and building of algorithms that simulate thousands of COLREG situations (encounter scenarios) is highly required considering the types of different ships (container, cargo, tanker, general cargo, RoRo, passenger, etc.), differences in kinematic and specification, and environmental conditions of sea and weather.
ii. Future studies need to prepare for the manned, unmanned, and autonomous ships encounter, i.e., the human–machine interaction at sea. It has been suggested that ship (manned and unmanned) encounters can be facilitated by following COLREG regulations, e-navigation and traffic-separated route networks [91].
iii. There is a need to build algorithms that can handle emergency scenarios or unforeseen circumstances thus being reactive and ensuring safety. Such tools would probably be identified after the operation of MASS.
iv. Ships differ in operations and conditions, and even in reaction to commands. Although the fundamentals of how different ships react autonomously to a variety of navigational conditions would follow the same assumptions; each vessel type (container, cargo, tanker, general cargo, roro, passenger, etc.) would need its specific models of intelligence command and control algorithms. This indicates the need to integrate the dynamics and kinematics of these ship types. Technically, this also means that the situational awareness system will have to be different as the reaction distance (time) of a large vessel is considerably higher; thus, higher predictability levels are needed [27].
v. Some of the path planning algorithms are restrained in capability due to impractical assumptions (i.e., open sea or only two ships encounter), thus ignoring environmental conditions and COLREGS [19]. In addition, most algorithms have been tested in simulations, but reliability is limited, thus, proving their validity in real-world scenarios still has to be tested. Moreover, encoding COLREGs within path planning and collision avoidance algorithms is particularly challenging in dynamic maritime environments, where AI must interpret complex, context-dependent rules. Current algorithms often assume simplified conditions, such as open seas or limited vessel interactions, and struggle to account for real-world variability. This limitation underscores the need for advanced AI approaches that can adapt to changing conditions and handle ambiguous encounters, as well as for extensive testing of these algorithms in real-world maritime settings to ensure safety and reliability.
vi. Studies widely addressed the ASV and USV, but very few addressed the oceangoing vessels and MASS. Although the application of such algorithms is valid for the OGV

(same fundamentals), investigation of applications of these algorithms in oceangoing vessels is highly recommended.

vii. The literature dedicates large efforts being utilised in machine learning algorithms (collision avoidance, obstacle detection, and motion control algorithms) separately. Information about systems and subsystem integration is still not available [43], although subsystem integration is essential for safety and interoperability. For example, algorithms do not talk to each other, in other words, there are issues with communication between algorithms, which may result in issues to avoid collisions [55]. This calls for system integrators to be integrated in MASS [3].

viii. The certification of artificial intelligence and machine learning (AI/ML)-based systems remains a significant challenge, particularly in the maritime domain, where safety-critical subsystems are increasingly reliant on these technologies. Drawing parallels with the aeronautic and railway industries, where certification processes are rigorous, it becomes evident that developing a framework for certifying AI/ML in MASS is essential to ensure reliability and safety. This represents an important avenue for future research and industry collaboration

The novelty of this study lies in its comprehensive investigation of autonomous navigation systems for Maritime Autonomous Surface Ships (MASS). Unlike previous research, this study presents an overarching framework that integrates all necessary components, including decision-making systems, situational awareness technologies, and sensor fusion, while also addressing cybersecurity challenges. By filling existing gaps, this study serves as a valuable resource for researchers and practitioners, guiding future research and prototype development in autonomous navigation and conventional shipping systems. The insights provided here can also help stakeholders prepare for the integration of autonomous navigation technologies, fostering more informed decisions about investments, regulations, and workforce development.

A key limitation of this study is the potential for subjective interpretation in the qualitative analysis, despite efforts to minimise bias through independent reviews and result comparison. Future studies should explore the skill requirements, environmental impacts, and infrastructure adaptations necessary to support the widespread adoption of autonomous navigation systems. While this study presents a unified architecture for Maritime Autonomous Surface Ships (MASS), further research is encouraged to explore and develop distinct, subsystem-specific architectures. Separate architectures for key subsystems—such as navigation, communication, and energy management—could provide deeper insights and allow for more specialised optimisations within each area. Given the predominant focus of existing studies on ASVs and USVs, there is a clear need for further research specifically addressing the unique challenges and requirements of Maritime Autonomous Surface Ships (MASS).

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Notes

[1] COLREGs is divided into three parts. Part A defines vessel and authority responsibilities, Part B regulates the conduct of vessels in an encounter, and Part C establishes communication protocols. Rules contained in Part B are defined as Steering and Sailing Rules, thus more important in CA [57].

[2] Examples of kinematic constraints is vessel turning radius which limit the turning angel, and dynamic is the turning radius or the stopping distance in conjunction with the speed.

[3] Rolls Royce icon DP system model is operational and ready.

[4] The ISO established a Working Group (WG10) on smart ships and marine technology, that is establish a common vocabulary and data model for MASS interoperability.

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