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Research paper

Integrating situation-aware knowledge maps and dynamic window approach for safe path planning by maritime autonomous surface ships

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ABSTRACT

This study investigates the enhancement of Maritime Autonomous Surface Ships (MASS) navigation and path-planning through the integration of ontology-based knowledge maps (KM) with the Dynamic Window Approach (DWA), a fusion termed KM-DWA. The ontology-based KM model is important for MASS navigation, offering a framework for situational awareness, including contextual information fusion and decision-making evidence. This research enriches the KM model with collision avoidance rules from the International Regulations for Preventing Collisions at Sea (COLREGs), building upon our previous work on MASS's efficient and COLREGs-compliant navigation in encounter scenarios. The model provides navigational context, covers COLREGs rules and environmental factors, and recommends MASS actions for various scenarios as suggested by COLREGs. Moreover, an adapted DWA, tailored to maritime navigation, accounts for specific constraints and safety measures for MASS, utilising KM-derived situational awareness as constraints in its cost function for path planning. A significant innovation introduced here is a tiered safety distance model featuring proactive, defensive, and collision buffers to ensure rule-compliant and effective collision avoidance. This scheme enables MASS to take timely collision avoidance actions at both proactive and defensive distances, in line with COLREGs recommendations. The effectiveness of the KM-DWA algorithm is validated by comparing it with the basic DWA algorithm in single- and multi-vessel encounter scenarios. The experiment outcomes illustrate the integrated approach's superiority in terms of COLREGs compliance and collision avoidance rate, emphasising its ability to support COLREGs-compliant decision-making and enhance situational awareness in autonomous maritime operations.

1. Introduction

1.1. Background

MASS has the potential to revolutionise the maritime industry, offering prospects for increased efficiency, cost reduction, and diminished environmental impact (Negenborn et al., 2023). However, the safe and effective operation of MASS in intricate and dynamic maritime settings poses considerable challenges, particularly in achieving advanced situational awareness comparable to that of human operators so that safe interactions can be ensured.

Recent research in MASS navigation explores innovative technologies to enhance maritime understanding and interaction. Within this domain, the ontology concept has emerged as a potent tool, facilitating the development of knowledge maps. These maps provide a structured and comprehensive representation of maritime information, advancing beyond the capabilities of conventional knowledge graphs.

1.2. Motivation

Building on this background, we delve into the critical aspect of situational awareness in MASS navigation, which is important for safe navigation, collision avoidance, and prompt decision-making in maritime contexts. This phase involves the interpretation of sensor data and information fusion to recognise and understand environmental elements and their interrelations, projecting future states and events (Endsley, 1995). Situational awareness thus forms the basis of decision-making processes in MASS.

In recent years, multiple approaches have been investigated to enhance situational awareness in MASS, including sensor fusion

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(Sanfilippo, 2017), machine learning, and knowledge representation (Song et al., 2023). Nonetheless, these methods frequently encounter challenges in handling uncertainties, integrating disparate data sources, and conforming to maritime regulations. Furthermore, existing literature often overlooks the intricate relationship between situational awareness and decision-making in MASS. This paper, building upon and extending our prior work (Song et al., 2022), aims to fill this gap.

Among the diverse methodologies aimed at enhancing situational awareness and navigation, the Dynamic Window Approach (DWA) stands out for its applicability in dynamic and uncertain environments. DWA, originally conceived for mobile robot navigation, optimises the navigational strategy by assessing the velocity space to avoid collisions while maintaining progress toward the goal. Adapting DWA to the maritime context requires consideration of the kinematic and physical constraints of vessels.

1.3. Objectives

The primary objective of this paper is to develop and validate an integrated approach that enhances the situational awareness and decision-making capabilities of MASS. This involves:

1. Integrating multi-source sensor data with maritime regulations through a knowledge maps model.
2. Developing a multi-tier distance collision avoidance concept tailored to COLREGs rules.
3. Enhancing path-planning and decision-making capabilities by integrating the knowledge maps model with the Dynamic Window Approach.

1.4. Contributions

The contributions of this paper are threefold:

1. **Advanced Knowledge Maps Model**: An advanced knowledge maps model that effectively combines multi-source sensor data with maritime regulations, offering a comprehensive solution for enhanced situational awareness in MASS.
2. **Multi-Tier Distance Collision Avoidance**: a novel multi-tier distance collision avoidance concept applicable to the COLREGs rules, including proactive distance, defensive distance, and collision distance, ensuring positive interaction with target vessels in maritime collision avoidance scenarios.
3. **Integration with DWA**: An integration of the ontology-based knowledge maps model with the Dynamic Window Approach, enhancing the path-planning and decision-making capabilities of MASS.

1.5. Structure of the paper

The remainder of this paper is organised as follows. Section 2 presents a comprehensive review of the literature on situational awareness, knowledge maps, ontologies, and decision-making in MASS, addressing existing methodologies and their limitations. Section 3 details the methodology employed in developing the knowledge maps model and its integration with the adapted DWA. Section 4 validates the proposed model through implementation and comparison with existing approaches. Section 5 presents the comparative results of path planning for the proposed model. Section 6 and Section 7, respectively, discuss the key findings and limitations of the methodology and summarise the main contributions and potential in the autonomous maritime systems domain.

2. Literature review

2.1. Situation awareness in the maritime domain

Situational Awareness (SA) is a human cognitive function that is important for strategic decision-making. Its role in human performance has been explored for many years in many domains (Endsley, 1995). In MASS, SA's role extends to integrating advanced sensor technologies, artificial intelligence, and knowledge maps. Since situational awareness is crucial for the safe navigation of unmanned vessels, the research conducted by (Thombre et al., 2022) focuses on sensor technology and distributed SA, which are the prerequisites for unmanned vessels to sense the environment during navigation accurately and can provide accurate data support for the situational awareness of unmanned vessels.

Recent advancements in MASS navigation, as explored by (Zhang et al., 2021), involve developing sophisticated collision-avoidance systems using SA. These systems predict and mitigate hazards, enhancing maritime safety. Knowledge maps have hereby become integral in MASS for decision-making and navigational accuracy. The integration of general maps and domain knowledge is discussed by (Song et al., 2022), illustrating the importance of comprehensive spatial information for navigational systems. The research conducted by (Sui et al., 2021) applies complex network theory to develop indicators that evaluate marine traffic, significantly contributing to situational awareness and the safety and efficiency of maritime navigation. Additionally, the critical role of these technologies in the realm of maritime education is underscored in (Deling et al., 2020), highlighting their necessity for preparing the future workforce. Moreover, a quantitative model for situational awareness tailored to address the complexities of maritime scenarios is presented in (Zhou et al., 2019), offering a robust framework for assessing and enhancing navigational decision-making processes.

In the existing body of research on situational awareness for MASS, there is a gap in the deployment of the knowledge map model that is capable of understanding the context of real-time maritime navigation. Such a model is important for the accurate interpretation of situational data, which, in turn, is crucial for making informed navigational decisions. Such a model should not only incorporate comprehensive spatial and regulatory information but also align with the dynamic decision-making requirements of MASS. The present study seeks to address this gap by proposing an extended knowledge map model tailored for collision avoidance of MASS, aiming to enhance rule compliance and safety of autonomous avoidance through improved situational awareness.

2.2. COLREGs-compliant decision-making

The advent of MASS necessitates a reevaluation of traditional maritime practices, particularly the application of COLREGs. These regulations for ensuring safety and preventing collisions must now be translated into a form comprehensible to autonomous systems. This section explores recent scholarly efforts in embedding COLREGs into the decision-making algorithms of unmanned vessels, as well as the current research needs.

- **Integration of COLREGs in Unmanned Navigation Systems**

Studies conducted by (Porathe, 2020) and (Zhang et al., 2022) emphasise the necessity for autonomous systems not only to recognise but also to actively comply with COLREGs. The use of fuzzy logic, as explored in (Lee and Kwon, 2004), presents an approach to interpreting these rules for autonomous navigation. Collectively, these studies demonstrate steps in integrating human-centric rules into machine-operable directives.

- **Collision Avoidance and Decision-Making in Multi-Vessel Encounters**

The complexity of multi-vessel encounters under COLREGs is a focal point of several studies. Research conducted by (Liu et al., 2019) delves into decision-making models and cooperative strategies for collision avoidance. The absence of specific COLREGs provisions for such scenarios, as discussed by (Wang et al., 2020), highlights a significant gap in current regulations, suggesting a need for expansion to accommodate the intricacies of autonomous navigation. The focus of the study conducted by (Huang et al., 2020) is on collision avoidance systems for autonomous ships, particularly considering uncertainties in ship dynamics. It highlights the challenges in parameter identification for ship dynamics and how these uncertainties can impact collision avoidance.

- **Advanced Control Systems and Artificial Intelligence in COLREGs Compliance**

A distributed control scheme for autonomous tugboats was proposed in (Du et al., 2022) and (Du et al., 2021a) to ensure collision avoidance in restricted water traffic environments while complying with COLREGs. It contributes to the field by tackling the challenge of collision avoidance in complex, interconnected vessel systems, which is a critical aspect of adhering to COLREGs in modern maritime operations. Furthermore, a multi-agent control scheme for managing the speed and coordination of multiple tugboats during ship towing was introduced in (Du et al., 2021b), addressing the complexities of multi-vessel operations and the necessity of coordinated actions.

The study conducted in (Huang et al., 2020b) proposes a framework of human-machine interaction for collision avoidance. The framework is tested with respect to its compliance with COLREGs, i.e., the presence of oscillations when the ship is underactuated versus the behaviour of COLREG compliance.

While existing research on integrating the COLREGs into autonomous maritime navigation systems has made great progress, particularly in compliance with power-driven vessels, they have tended to focus on a subset of the regulations, for example, Rules 13, 14 and 15 (Du et al., 2022). Such analyses are less concerned with including COLREGs rules for target vessel manoeuvrability and proactive avoidance rules in collision avoidance, which are pivotal in determining the priority of way and executing explicit and effective evasive manoeuvres. Our research aims to address this limitation by incorporating a more comprehensive interpretation of COLREGs, including consideration of target vessel manoeuvring capabilities, vessel type, and proactive collision avoidance strategies in different encounter scenarios, into the decision-making frameworks.

2.3. DWA-based path-planning in MASS

DWA, a seminal concept in robotics introduced for robotics navigation by (Fox et al., 1997), selects the optimal velocity of a robot from a set of feasible velocities within a “dynamic window” based on the robot’s current state and a cost function evaluating safety, efficiency, and goal reachability. The process ensures real-time collision avoidance and goal-oriented movement by continuously updating the robot’s trajectory. Its core advantage lies in its computational efficiency and adaptability to rapid changes, making it very suitable for dynamic environments.

DWA’s journey from theory to wide-ranging applications reflects its robustness and versatility. Its application in high-speed navigation was demonstrated in (Brock and Khatib, 1999), revealing its capacity for quick adaptation in fast-paced scenarios. Its scope with an adaptive variant was expanded in (Dobrevski and Skocaj, 2020), highlighting its customizability to diverse robotic architectures. Its real-world feasibility through practical application in robotic navigation was underscored in (Maroti et al., 2013) by testing the effectiveness of a proposed collision-checking algorithm combined with the DWA algorithm.

The transition of DWA into maritime domains, particularly in MASS, marks a new chapter in its application. DWA’s role in enhancing navigational safety in autonomous maritime systems was highlighted in (Öztürk et al., 2022). The integration of DWA with a Shark-Inspired Algorithm by (Liang and Liu, 2023) and its fusion with the A-Star algorithm by (Guan and Wang, 2023) demonstrate its adaptability in maritime environments, blending traditional algorithms with advanced techniques for optimal path planning. Its adaptability to environments with dynamic obstacles was emphasised in (Chen et al., 2019).

DWA is a pivotal method for real-time collision avoidance and path optimisation in robotics, valued for its computational efficiency and ability to adapt to dynamic changes. However, its application within the maritime domain faces challenges due to the unique kinetics and physical constraints required for MASS movement. This necessitates modifications to the DWA algorithm in order to ensure it aligns with maritime navigation, indicating a gap between its current capabilities and the demands of maritime application.

3. Methodology

Following the research needs and gaps as outlined in the previous section, the research methodology of this study is divided into three main parts: the development of the ontology-based knowledge map, the adaptation of DWA for MASS’s navigation, and the integration of these two components.

3.1. Development of the ontology-based knowledge map

The ontology-based knowledge maps model is developed to enhance the situational awareness of MASS. The map is a semantic graph formed by multiple entities and the relationships among them. The knowledge map model integrates various maritime navigation rules and environmental factors, specifically focusing on COLREGs. The model provides the following three capabilities to support the safe navigation of MASS.

1. **Task awareness** refers to high-level information from maritime regulations, collision avoidance, planned long- and short-term routes, communications with authorities and surrounding ships, etc., which serve as inputs to the ship’s KM comprehension module. It is compiled and interpreted in a semantic format to support the MASS’s decision-making. See the example below, where MASS is aware of the destination by understanding the route first via "`#MASS`" "`#has_planned_routes`" “`Planned_route`”, and then finalise the understanding of its destination via "`#destinationLoc`” as an instance of "`#Planned_route`”. The awareness results are organised in an XML format to facilitate knowledge management by MASS.

```
<owl:DatatypeProperty rdf:about="#destinationLoc">
  <rdf:type rdf:resource="http://xxx/owl#FunctionalProperty"/>
  <rdfs:domain rdf:resource="#Planned_route"/>
  <rdfs:range rdf:resource="http://xxx/XMLSchema#string"/>
</owl:DatatypeProperty>
```

```
<owl:ObjectProperty rdf:about="#has_planned_routes">
  <rdfs:subPropertyOf rdf:resource="http://xxx/owl#topObjectProperty"/>
  <rdfs:domain rdf:resource="#MASS"/>
  <rdfs:range rdf:resource="#Planned_route"/>
</owl:ObjectProperty>
```

2. **Control System Constraints**: The control system of MASS receives the outputs of the knowledge maps model as constraints, such as the situational information provided by the KM and the decision actions suggested by the COLREGs in the collision avoidance scenarios, where the situational information includes the type of scenario encountered such as crossing, and the suggested actions include turning to the starboard side or going straight ahead. These outputs

serve as constraints for the controller or planner, such as the space available for acceleration and turn rate at the next moment, which affects the subsequent decision actions of the ship.

3. **Navigational Status Synthesis** involves the aggregation of basic navigational and environmental data surrounding the vessel. These two pieces of data are continuously fed into the perception of the KM model for data processing as well as relationship formulation and further fed into the comprehension module to form semantic information that facilitates the real-time construction of situational awareness semantic graphs. The capability of Navigational Status Synthesis supports the representation of the key concepts and relationships related to navigation at the current moment or over a period of time.

An enhanced ontology-based Knowledge Management model is presented in this study, building upon a foundational knowledge maps model introduced in (Song et al., 2022). In that prior work, a Situational Awareness-based KM model was developed for MASS, aiming at creating a comprehensive, real-time knowledge base. This base was designed to encapsulate both external information and internal data, including the control system, navigational tasks, and status, with its comprehensive details documented in (Song et al., 2022).

The construction of the KM model employs ontology tools grounded in a thorough analysis of situational requirements. This process involved identifying key navigation-related elements of MASS and categorising them into classes, object properties, and data properties. Initially validated through basic scenario tests, the model has now been enhanced to address real-world applications. This enhancement includes the integration of an enriched KM model within the path planner. This model incorporates a broader spectrum of rules for collision avoidance, including the conversion and coordination of multiple COLREGs rules, elements not previously considered in our initial model.

Our aim is to incorporate more COLREGs rules in our model so that MASS can be better adapted to the various navigational environments, especially in those areas full of COLREGs, for example, the harbour area, traffic separation area, etc.

In order to incorporate collision rules in the knowledge map, we introduced Semantic Web Rule Language (SWRL) in the model, which provides a convenient way to convert statements into machine-readable language. Specifically, key collision avoidance rules for ships in sight of one another in COLREGs are considered in this paper, incorporating Rules 11, 13, 14, 15, 16, 17 (a(i), a (ii), b, d), 18 (a,b,c).

The translation details of COLREGs rules based on SWRL are given in Appendix Table 2.

3.2. DWA adaptation for MASS

The classic DWA algorithm is mostly used for two-wheel robot navigation. For MASS, especially for the three degrees of freedom (3DOF) MASS, which has not only the force from the X axis and the moment from the Z axis but also the force from the Y axis, the DWA needs to be adapted.

3.2.1. Acceleration-based velocity sampling

To better consider the motion characteristic of MASS, the sampling method proposed in (Missura and Bennewitz, 2019), which uses an acceleration-sampling method, is introduced here. The illustration for sampling acceleration in DWA can be seen in Fig. 1, where $V_s, V_r, and\ V_d$ represent the space of possible velocities, the space of possible velocities constrained by its acceleration, and the intersection of the restricted areas, namely V_s, and V_r. By incorporating the vessel's dynamic capabilities, velocities obtained based on acceleration sampling are computed from the vessel's current velocity: $[a_{u\_min}, a_{u\_max}]$, $[a_{v\_min}, a_{v\_max}]$ and $[a_{\omega\_min}, a_{\omega\_max}]$, where a_{u_min}, a_{v_min}, a_{ω_min} refer to the minimum accelerations from the direction of surge, sway, and yaw axis, respectively, while a_{u_max}, a_{v_max}, a_{ω_max} refer to the maximum

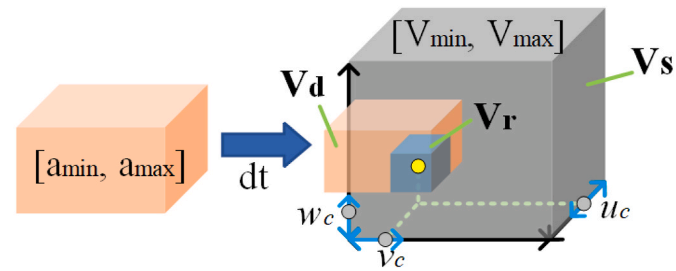


Fig. 1. The schematic for sampling accelerations in the surge, sway, and yaw directions in the DWA algorithm.

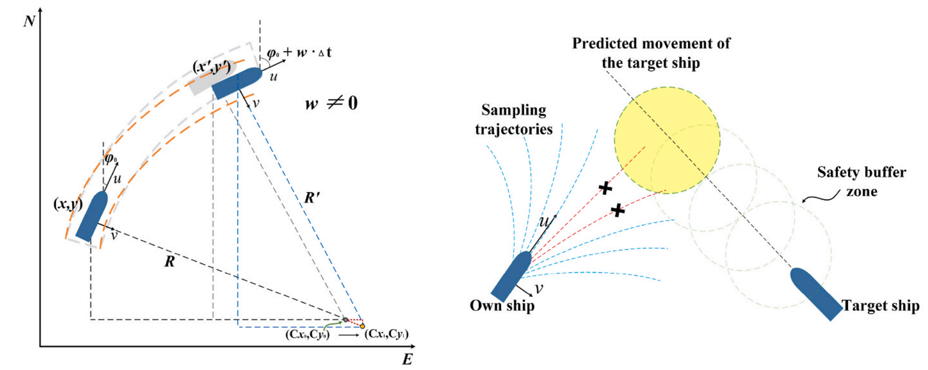
accelerations along the directions of surge, sway, and yaw, respectively. Thus, new velocities $u_{t+\Delta t}$, $v_{t+\Delta t}$, and $\omega_{t+\Delta t}$ are derived using: $u_{t+\Delta t} = u_t + a_u{\cdot}\Delta t$, $v_{t+\Delta t} = v_t + a_v{\cdot}\Delta t$, and $\omega_{t+\Delta t} = \omega_t + a_\omega{\cdot}\Delta t$, where Δt is the time step, u_t and a_u are current surge velocity and acceleration, v_t and a_v are current sway velocity and acceleration, ω_t and a_ω are current yaw velocity and acceleration. The velocity space is discretised into potential velocities, constrained within the vessel's maximum and minimum speed limits, forming a cubic space: $V_s = \{[u_{\min}, u_{\max}], [v_{\min}, v_{\max}], [\omega_{\min}, \omega_{\max}]\}$, where $u_{\min}$, $v_{\min}$, and $\omega_{\min}$ refer to the minimum velocities from the direction of surge, sway, and yaw axis, respectively, while $u_{\max}$, $v_{\max}$, $\omega_{\max}$ refer to the maximum velocities along the directions of surge, sway, and yaw, respectively. Additionally, during the vessel's navigation, each velocity pair (u, v, ω) within this space is evaluated for feasibility based on the cubic space constraints, and optimality is evaluated based on the total benefit of cost functions determined by sampling the velocity pairs.

Key differences and advantages of acceleration-based sampling over velocity-based sampling in the maritime context include the following.

1. Acceleration-based sampling aligns with the vessel's current motion state, offering realistic velocity options that reflect the vessel's physical capability for speed and directional changes.
2. Acceleration-based sampling models more accurately the vessel's motion than the velocity-based sampling method, accounting for realistic acceleration and deceleration rates, which are important in dynamic maritime environments.

3.2.2. Prediction of MASS movement in DWA

In this part, the focus shifts to predicting the movement of MASS using the DWA. The introduction of a force along the Y-axis adds complexity to the predicted motion trajectory of the object. Unlike the classic DWA algorithm, which primarily relies on linear and angular velocities to predict linear or circular motion, the presence of Y-axis linear velocity introduces additional dimensions to the motion trajectory analysis. This change has resulted in the prediction of vessel motions that will not be conventional linear or circular paths. In order to simplify this problem, assuming the MASS will still do the circular movement during a small period, we revise the algorithm by amending the centre of rotation by moving it from the original point $(C_{t\_x_0}; C_{t\_y_0})$ to the current one $(C_{t\_x_1}; C_{t\_y_1})$ because of the influence of the sway velocity. The scheme diagram is shown in Fig. 2 - (a) when the yaw velocity ω_t does not equal 0, where (ϕ_t) and $(\phi_t + \omega_t \cdot \Delta t)$ represent the original angle at time t and the angle after moving, respectively. u_t and v_t represent the surge and sway velocity at time t, which do not change during the small period. Point $(C_{t\_x_0}; C_{t\_y_0})$ is the original rotation centre, and point $(C_{t\_x_1}; C_{t\_y_1})$ is the new rotation centre, which moves from the former to the current one under the influence of the sway velocity. R_t and R_t' are calculated based on the classic DWA algorithm and simplified extensive DWA tailored for MASS. Additionally, (x_t, y_t) and $(x_{t+\Delta t}; y_{t+\Delta t})$ refer to the start point and the predicted point after Δt, respectively. The equations for calculating them are as follows:



(a) Assumption of MASS for circular motion (b) Extended DWA algorithm with collision avoidance prediction

Fig. 2. The schematic diagram of the revised DWA algorithm for MASS.

$$R_t = \frac{u_t}{\omega_t}; \quad R_t' = R_t + v_t \bullet \Delta t$$

$$C_{t\_x_0} = x_t - R_t \bullet \sin(\phi_t); \quad C_{t\_y_0} = y_t + R_t \bullet \cos(\phi_t)$$

$$C_{t\_x_1} = C_{t\_x_0} + v_t \bullet \Delta t \bullet \cos(\phi_t); \quad C_{t\_y_1} = C_{t\_y_0} - v_t \bullet \Delta t \bullet \sin(\phi_t)$$

$$x_{t+\Delta t} = C_{t\_x_1} - R_t' \bullet \cos(\phi_t + \omega_t \bullet \Delta t); \quad y_{t+\Delta t} = C_{t\_y_1} + R_t' \bullet \sin(\phi_t + \omega_t \bullet \Delta t)$$

Regarding collision avoidance between ships, the collision prevention distance determined according to the classic DWA algorithm is different from the complex motion and longer stopping distances of MASS, influenced by maritime forces and vessel inertia. Thus, we extend the classic algorithm to a predicted collision avoidance algorithm, as seen in Fig. 2 - (b). The sampling trajectories of the own ship touching the safety buffer of the predicted motion of the target ship will be removed. The core principle of DWA involves the generation of a velocity space, considering a robot's current velocity and acceleration limits. The following equations define the velocity space:

$$V_s = \{(u, v, \omega) | u_{min} \le u \le u_{max}, v_{min} \le v \le v_{max}, \omega_{min} \le \omega \le \omega_{max}\},$$

$$V_d = ((u, v, \omega) | u \in [u_t - a_u \bullet \Delta t, u_t + a_u \bullet \Delta t], v \in [v_t - a_v \bullet \Delta t, v_t + a_v \bullet \Delta t], \omega \in [\omega_t - a_\omega \bullet \Delta t, \omega_t + a_\omega \bullet \Delta t]),$$

where V_s represents the set of all achievable velocities, u is the surge velocity, v is the sway velocity, ω is the yaw velocity, and V_d is the dynamic window, which considers the MASS's acceleration limits.

The algorithm evaluates each acceleration pair (a_u, a_v, a_ω) within the reachable velocity range (u, v, ω) using aa comprehensive cost function. This cost function incorporates several objectives, including goal-reaching, obstacle avoidance, path-keeping, time to the goal, and compliance with COLREGs compliance. The optimal set of acceleration $(a_u^*, a_v^*, a_\omega^*)$ and optimal velocity (u^*, v^*, ω^*) that minimise this cost function are then chosen for execution, see Equations (1) and (2). The cost function for each acceleration vector, denoted as $C(a_u, a_v, a_\omega)$, is weighted by coefficients α_i, which reflect the importance of various objectives such as safety, efficiency, and rule adherence.

$$(a_u^*, a_v^*, a_\omega^*) = \arg \min_{(a_u, a_v, a_\omega) \in a_d \& a_s} C(a_u, a_v, a_\omega), C(a_u, a_v, a_\omega) = \sigma\left(\sum_{i=1} \alpha_i \bullet C_i(a_u, a_v, a_\omega)\right) \tag{1}$$

$$(u^*, v^*, \omega^*) = (u_t, v_t, \omega_t) + (a_u^*, a_v^*, a_\omega^*) \bullet \Delta t \tag{2}$$

To implement the DWA algorithm on MASS effectively using an acceleration-based sampling technique, the algorithm compares various combinations of accelerations within a discretised sampling space. This procedure entails enumerating potential acceleration vectors that are feasible within the dynamic limitations of the vessel and environmental constraints. For each sampled acceleration vector, the algorithm calculates the resultant velocities.

Subsequently, the acceleration vector $(a_u^*, a_v^*, a_\omega^*)$ that yields the lowest cumulative cost, indicative of the optimal trajectory under current conditions, is selected. This optimal acceleration vector is then utilised to derive the corresponding optimal velocity (u^*, v^*, ω^*), which guides the MASS towards its target while prioritising safety, efficiency, and regulatory compliance. Furthermore, this selection process is iterative. By systematically analysing the cost associated with each pair of acceleration and velocity, the algorithm ensures that the MASS can adapt its navigation strategy in real-time, optimising for the most favourable outcome based on the current situational context.

3.3. Integration of knowledge maps and DWA

In this section, the integration of an ontology-driven KM with a refined DWA algorithm, KM-DWA, is introduced.

3.3.1. System architecture

The KM-DWA architecture consists of three modules: knowledge maps, DWA path planner, and trajectory generator. The formation process of the knowledge maps is presented in Algorithm 1. Before processing real-time data, the KM, an XML file used to represent ontology-based KM, needs to be aware of tasks, including route, departure, destination, etc. The XML file contains the concepts and relationships involved in ship navigation, encoded into various classes and properties. Refer to (Song et al., 2022) for details. MASS, Task, Instance, and **Object Property**, representing the operators of the ontology, namely classes, instance, and objective property, etc., used to instantiate and transform the navigation-related information into the ontology. The own ship $[OS]$, i-th task $[Task_i]$ and the relationship between the own ship and $Task_i$: $\{hasTask_i\}$ are the results of the instantiation. In addition, SWRL is used here to convert COLREGs into machine-understandable rules, that is, the rules that ships need to comply with and the actions recommended by the rules if they satisfy a specific set of conditions. At this point, the generated KM file will be used for real-time situational understanding. First, the KM module continuously receives environmental information EI_t, such as visibility, target vessel information etc., and navigation information NI_t generated by the trajectory generator, such as the *position, speed, and heading* of the own ship. These data are fed into the Perception module of the KM model, where data processing is performed to generate parameter information used for situation analysis, which will be passed to the

Projection module and Comprehension module for further analysis. Specifically, Projection performs the task of risk evaluation, which is to determine whether there is a potential collision risk based on whether DCPA and TCPA reach the pre-set thresholds. Then, the risk estimate generated by Projection is passed into the Comprehension module to update the situational information in the ontology file, including repeating the ontology operation instantiation process as in steps 6 to 7 in Algorithm 1 to generate the situational information at time t. Then, the Pellet inference engine is called to reason about the parameter information obtained by the Perception module and the risk assessment results of the Projection, the tasks, and the rules that need to be followed to clarify the rules that need to be obeyed, encounter scenarios and other information of $SAInfo_t$, details can be seen in Fig. 3. Then, situation information and tasks are passed into the planner as constraints, and the planner evaluates the optimal accelerations through sampling. The optimal acceleration obtained will be input into the trajectory generator to update the motion parameters at the next moment, including speed, heading, position and other information. The above process is repeated until the goal is achieved or a collision occurs.

In summary, obstacle avoidance by the KM-DWA algorithm is facilitated through the support of real-time knowledge maps. The real-time knowledge maps enhance task awareness and real-time situational understanding and provide crucial information that allows the KM-DWA algorithm to dynamically adjust its path, ensuring effective obstacle avoidance while considering the overall situational context.

$$\alpha = \frac{\pi}{2} - arctan\left(\frac{(y_{ob} - y_t)}{(x_{ob} - x_t)}\right) - \phi_t;\ \phi = \phi_{obt} - \phi_t - \pi$$

where ϕ_{obt} represents the heading of the target ship at time t, $\overrightarrow{P}_{ob} = (x_{ob}, y_{ob})$ represents the position of the target ship at time t.

Based on the six small circles divided into different coloured sections determined by the encounter angle and relative bearing, the type of encounter, such as "crossing", and the navigational priority of my ship, such as "give-way", can be determined, details can be seen in Fig. 4 (b). The six small circles in the figure are the division of the encounter angle, where different colours indicate different scenarios, the divisions in the blue zone are the sections of the relative bearing of the target ship relative to the own ship, and the dotted circles indicate three distances for collision avoidance, including proactive distance, defensive, and collision distances. Specifically, the *proactive distance* is the distance at which a "give-way" vessel is required to take collision avoidance action, while the "stand-on" vessel is required to maintain course and speed in accordance with the rules. The *defensive distance* is the distance at which the "stand-on" vessel is required to take evasive action when the "give-way" vessel does not take evasive action from the proactive distance to the defensive distance or when the evasion task cannot be accomplished by the "give-way" ship alone. The *collision distance* is the distance at which a collision between ships occurs.

Additionally, in order to address the need for effective collision avoidance, the three-tier safety buffer, i.e. proactive, defensive, and collision distances, is embedded within the DWA algorithm (see Algorithm 2) to satisfy the requirements of Rule 8 of COLREGs, that is *the action taken should be positive, made in ample time, and large enough to be readily apparent to another vessel observing visually or by radar*. COLREGs dictate distinct actions and timings for vessels operating as either the give-way vessel or the stand-on vessel.

Algorithm 1. Formation Of Knowledge Maps For Supporting Safe Navigation Of MASS

```
Input: Navigational Rules, Tasks, Environment information (EI_t), Navigational information (NI_t) of MASS(OS)
Output: Real-time knowledge maps in the form of situational semantic network
      Step 1: Task awareness
1:    Initialise the Knowledge Maps as an XML file.
2:    Formulate the Knowledge Maps: KM ← {{class, object properties and data properties}, ⋯ }
3:    Transform and add the task-related information, e.g., planned routes, waypoints, etc.
4:    Initialise the own ship: Instance: [OS] ← (MASS{OS}, DataProperties{OS})
5:    for each task Task_i do
6:        | Instance: [Task_i] ← (Task{Task_i}, DataProperties{Task_i})
7:        | Object Property{hasTask_i} ← ([OS], [Task_i])
8:        | Task = {[Task_i], ⋯ }
9:    Interpret navigational rules (COLREGs) as executable orders (turning to port or starboard) and add them to KM.
10:   for each rule Rule_x, do:
11:       |     Rule_x, RecommendAction_k ← SWRL(ship, condition_j, condition_{j+1}, ⋯ )
12:       |     Rule = {(Rule_x, RecommendAction_k), ⋯ }
13:   Store the Knowledge Maps file.
      Step 2: Real-time situation understanding
14:   While not colliding or reaching the destination, do:
          | // Navigational Status Synthesis
15:       | Obtain navigational information NI_t and environment information EI_t
16:       | Initialise: NI_t ← (Position_t, Velocity_t, Heading_t), EI_t ← (Visibility_t, targetVessels_t, ⋯ )
17:       | Perception
18:       |     SituationalParameters_t: {Encounter angle, DCPA, TCPA, ⋯ } ← SA(NI_t, EI_t)
19:       | Projection (risk evaluation): Risk_t ← Situational parameters
20:       | Comprehension:
21:       | Update KM: Add Instances, Object Properties, and Data Properties to KM as the steps: 6 → 7
22:       | SAInfo_t: {Regulation compliance, Encounter type, COLREGs role, CA distance, Recommended action} ←
          |     Reasoning_PelletReasoner{Situational parameters, Risk, Task, Rule}
          |
          | // Navigational Status Synthesis
23:       | Constraints of the Planner: AccelerationSamplingSpace_{t+1} ← {SAInfo_t, Task}
24:       | Optimise accelerations: OptimalAccelerations_{t+1} ← DWAPlanner(AccelerationSamplingSpace_{t+1})
25:       | Update velocities and heading: Velocity_{t+1}, Heading_t, ← Velocity_t, OptimalAccelerations_{t+1}
26:       | Update position: Position_{t+1} ← (Position_t, Velocity_t, Heading_t, Velocity_{t+1}, Heading_t)
      End
27    Return Real-time knowledge maps to provide guided information for the planner
```

3.3.2. Integrated collision avoidance scheme

The safe navigation of MASS hinges on their ability to accurately identify current situations and make decisions compliant with the COLREGs. Our methodology, derived from (Namgung, 2022), enables MASS to identify encounter scenarios through the calculation of encounter angles and relative bearings when a target vessel enters the detection range. The calculations of the Encounter angle (ϕ) and Relative bearing (α) (see Fig. 4 (a)) are as follows.

Distance Closest Point of Approach (DCPA) and Time Closest Point of Approach (TCPA) are further incorporated into the algorithm, ensuring that avoidance manoeuvres are not solely based on physical proximity but also on the timing of potential vessel convergence. Should either DCPA or TCPA fall below their respective thresholds, namely 3 m for

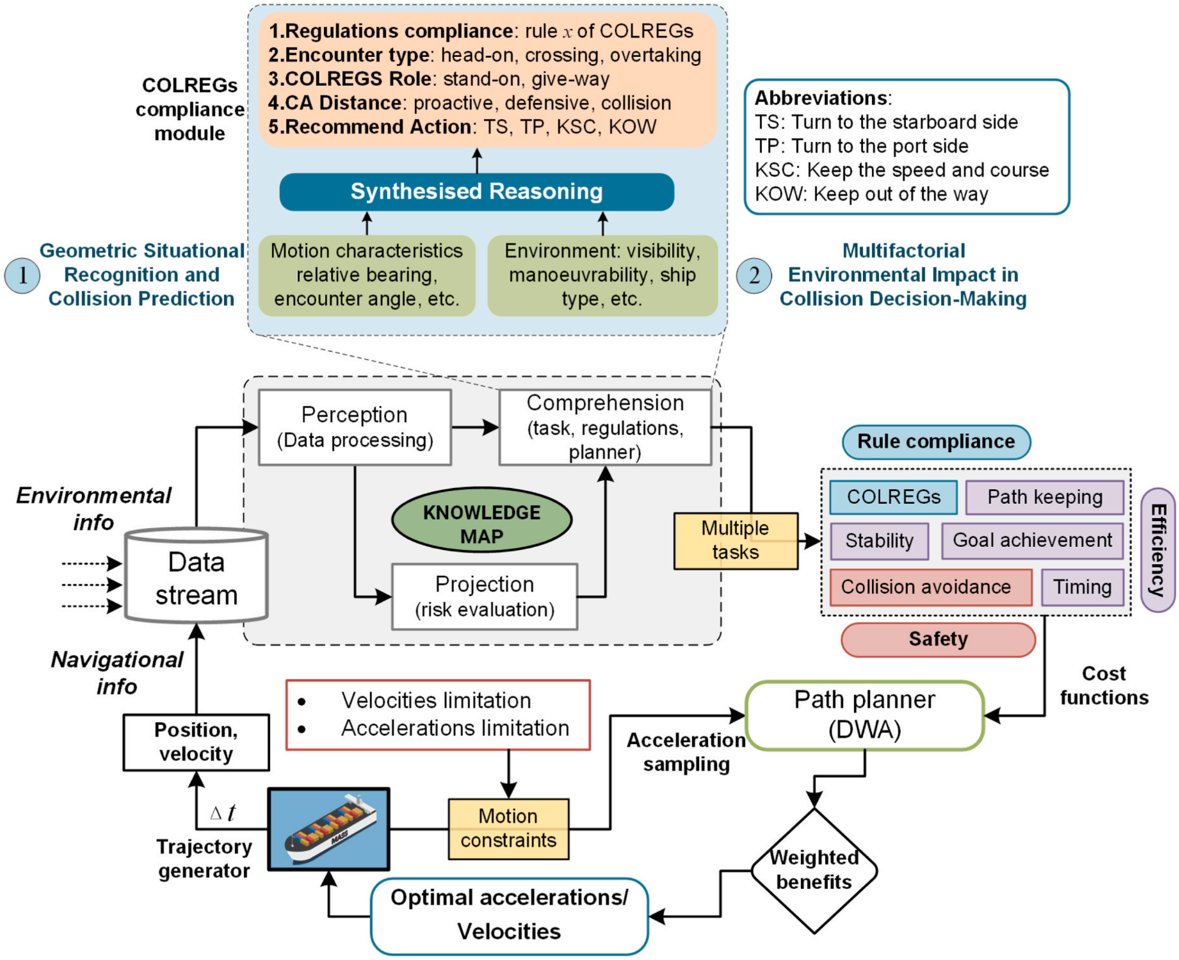


Fig. 3. The diagram of the KM-DWA decision-making framework based on the knowledge maps and DWA algorithm.

DCPA and 10 s for TCPA with respect to our model ship, the algorithm triggers the necessary avoidance manoeuvres, offering a dynamic and responsive framework for collision avoidance.

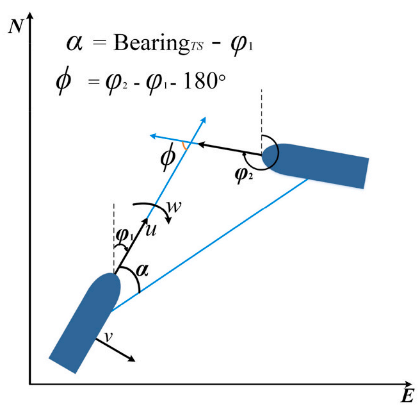
Algorithm 2. Determination Of Collision Avoidance Distance And Action For MASS

Input: *DCPA_threshold, TCPA_threshold,* $D_{collision}, D_{pro}, D_{def}$
Output: *Distance and recommended action to avoid collision*

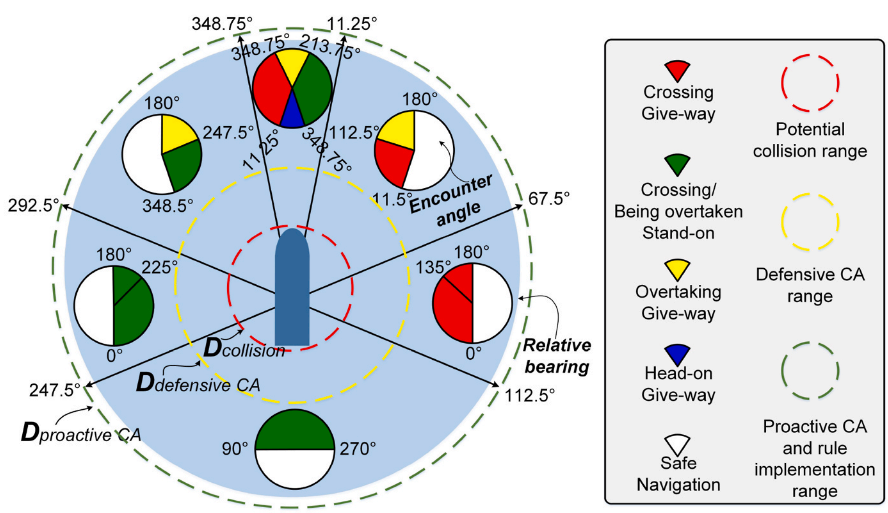
Get current distance $d_{current}$, *DCPA*, *TCPA*
if $d_{current} < D_{collision}$ ***then***
  Trigger: *Imminent collision avoidance, none*
else if $d_{current} < D_{pro}$ ***then***
  if *Own_action = "give_way"* ***then***
    Trigger: *Proactive collision avoidance, take evasive action*
  else if *Own_action = "stand-on"* ***then***
    Trigger: *Proactive collision avoidance, maintain course and speed*
else if $d_{current} < D_{def}$ ***then***
  if *Own_action = "stand-on"* ***and*** *(DCPA < DCPA_threshold and TCPA< TCPA_threshold)* ***then***
    Trigger: *Defensive collision avoidance, initiate independent action*
  else
    Continue: *Proactive collision avoidance, maintain course and speed*
else
  if *DCPA < DCPA_threshold* ***and*** *TCPA< TCPA_threshold* ***then***
    Trigger: *Collision avoidance, none*
  else
    Monitor: *Normal navigation, none*
Return *Distance and recommended action to avoid collision*

3.3.3. KM-DWA algorithm

The overarching goal of the KM-DWA algorithm is to obtain the best velocities for the action in the next time step. The best velocities can be calculated by the highest cost score by calculating different kinds of cost functions involving safety (collision avoidance), efficiency (Goal achievement, Path keeping, Time to goal, Stability), and rule compliance (COLREGs), as seen in Fig. 3. The details of the algorithm can be seen in Algorithm 3.



(a) Encounter angle and relative bearing



(b) Encounter scenarios determination based on the encounter angle and the relative bearing

Fig. 4. The illustration of sector division for collision scenario recognition.

Algorithm 3. KM-DWA For Path-Planning Of MASS

Input: $(x_t, y_t)\ (u_t, v_t, \omega_t)$, φ_t, **ob**, $T_{horizon}$, $goal$, $weights$, $D_{collision}$, D_{pro}, D_{def}
Output: *Optimal path*
Get current distance $d_{current}$, $DCPA$, $TCPA$
Function $f_{cost} = (pos, \mathbf{ob}, goal, weights, D_{collision}, D_{pro}, D_{def})$
  | ***return:*** *Total cost*
Function $f_{pred\_ob} = (\mathbf{ob}, time)$
  | ***return:*** *Predicted positions of obstacles after time*
Function $f_{pred\_os} = (pos, velocity, heading, acceleration, T_{horizon})$
  | ***return:*** *The predicted position of the own ship after time*
Function $f_{planning} = (goal, \mathbf{ob}, x_t, y_t, T_{horizon})$
  | ***Initialise*** *Optimal Cost:* $C^* \leftarrow -\infty$,
  | *SampleNum*← 8 //*Number of samples of each acceleration*
  | ***for*** *each acceleration combination* (a_u, a_v, a_ω) **do**
  | | $a_c \leftarrow (a_u, a_v, a_\omega)$
  | | $(x_{t+\Delta t}, y_{t+\Delta t}) \leftarrow f_{pred\_os}(x_t, y_t, u_t, v_t, \omega_t, \varphi_t, a_c, T_{horizon})$
  | | $(x_{ob_{t+\Delta t}}, y_{ob_{t+\Delta t}}) \leftarrow f_{pred\_ob}(\mathbf{ob}, T_{horizon})$
  | | *Cost* $C \leftarrow f_{cost}(x_{t+\Delta t}, y_{t+\Delta t}, x_{ob_{t+\Delta t}}, y_{ob_{t+\Delta t}}, goal, weights, D_{collision}, D_{pro}, D_{def})$
  | | ***if*** $C > C^*$ ***then***
  | | | $C^* \leftarrow C$
  | | | $a^* \leftarrow a$
  | | | $v^* \leftarrow v$
  | ***Return*** v^*
While the *goal is not true* ***do:***
  | *Optimal velocities* $v^* \leftarrow f_{planning}(goal, \mathbf{ob}, x_t, y_t, T_{horizon})$
  | *Update the next optimal position*
Return *Optimal path*

The mathematical expressions to calculate the total benefit cost at the next time step $t + \Delta t$ in a discrete space are as follows, where the accelerations (a_u, a_v, a_ω) are constant during Δt.

1. **Goal Achievement Cost Function**:

$$C_{goal}(t+\Delta t) = \left\| \overrightarrow{P}_{pred} - \overrightarrow{P}_{goal} \right\| \tag{3}$$

where $\overrightarrow{P}_t = (x_t, y_t)$ represents the position of MASS at time t, $\overrightarrow{P}_{goal} = (x_{goal}, y_{goal})$ represents the goal position to be reached by MASS, $\overrightarrow{P}_{pred} = (x_{t+\Delta t}, y_{t+\Delta t})$ represents the predicted position.

2. **Obstacle Avoidance Cost Function**:

$$C_{obstacle}(t+\Delta t) = \begin{cases} D_{min} - D_{obs} & if\ D_{min} < D_{obs} \\ 0 & otherwise \end{cases} \tag{4}$$

where D_{obs} is the distance to the nearest obstacle on the predicted trajectory at time $t+\Delta t$; $D_{\min}$ is the minimum safe distance at time $t+\Delta t$, which is set to be four times the length of the ship hull.

3. **Path Keeping Cost Function**:

$$C_{pathKeeping}(t+\Delta t) = e_{path} \tag{5}$$

where e_{path} is the deviation distance from the candidate point to the planned path.

4. **Time to Goal Cost Function**:

$$C_{timeToGoal}(t+\Delta t) = \left(\frac{\left\| \overrightarrow{P}_{pred} - \overrightarrow{P}_{goal} \right\|}{\sqrt{u_c^2 + v_c^2} + \varepsilon} \right) \tag{6}$$

where u_c *and* v_c are the candidate surge and sway velocities $t + \Delta t$, respectively.

5. **Navigation Stability Cost Function**:

$$C_{stability}(t+\Delta t) = (\phi_{pred} - \phi_t)^2 \tag{7}$$

where ϕ_{pred} refers to the predicted heading angle after Δt, $\phi_{pred} - \phi_t$ is the change in heading angle.

6. **COLREGs Compliance Cost Function**:

$$C_{colregs}(t+\Delta t) = \begin{cases} min(0, -\omega_c) & if\ Encounter\ type = "Crossing"\ and\ Own\ action = "give-way" \\ |u_c - u_t| + |v_c - v_t| + |\omega_c| & if\ Encounter\ type = "Crossing"\ and\ Own\ action = "stand-on" \\ min(0, -\omega_c) & if\ Encounter\ type = "Head-on" \\ 0 & otherwise \end{cases} \tag{8}$$

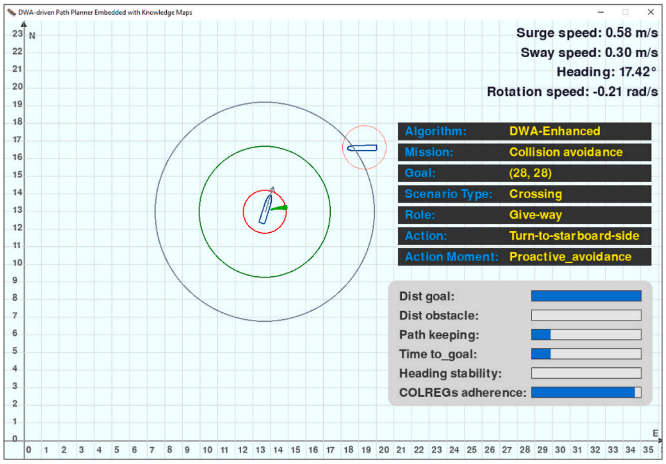


Fig. 5. The interface designed for simulation in the collision avoidance scenarios.

where u_c, v_c, ω_c represent candidate surge, sway, and yaw velocities, respectively. u_t *and* v_t denote the current surge and sway velocities, respectively.

The overall benefit function is then defined as a weighted sum of the individual cost functions from Equation (3) through to Equation (8), which is minimised to select the smallest combination of accelerations, as shown in Equation (1).

$$C(t+\Delta t) = \sigma\big(\alpha \bullet C_{goal}(t+\Delta t) + \beta \bullet C_{obstacle}(t+\Delta t) + \gamma \bullet C_{pathKeeping}(t+\Delta t) + \delta \bullet C_{timeToGoal}(t+\Delta t) + \eta \bullet C_{colregs}(t+\Delta t) + \kappa \bullet C_{stability}(t+\Delta t)\big) \tag{9}$$

where $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, $\boldsymbol{\gamma}$, $\boldsymbol{\delta}$, $\boldsymbol{\eta}$, $\boldsymbol{\kappa}$ are the weighting factors for each cost function. In this study, a combination of empirical testing and consideration for the importance of each function in relation to the overall goal of the algorithm was employed.

In adjusting the weighting factors, all weights were initially set to 1 to test if the vessel could successfully avoid collisions. It was observed that the vessel adhered too strictly to its planned route and failed to manoeuvre adequately, leading to collisions. This issue was evident with

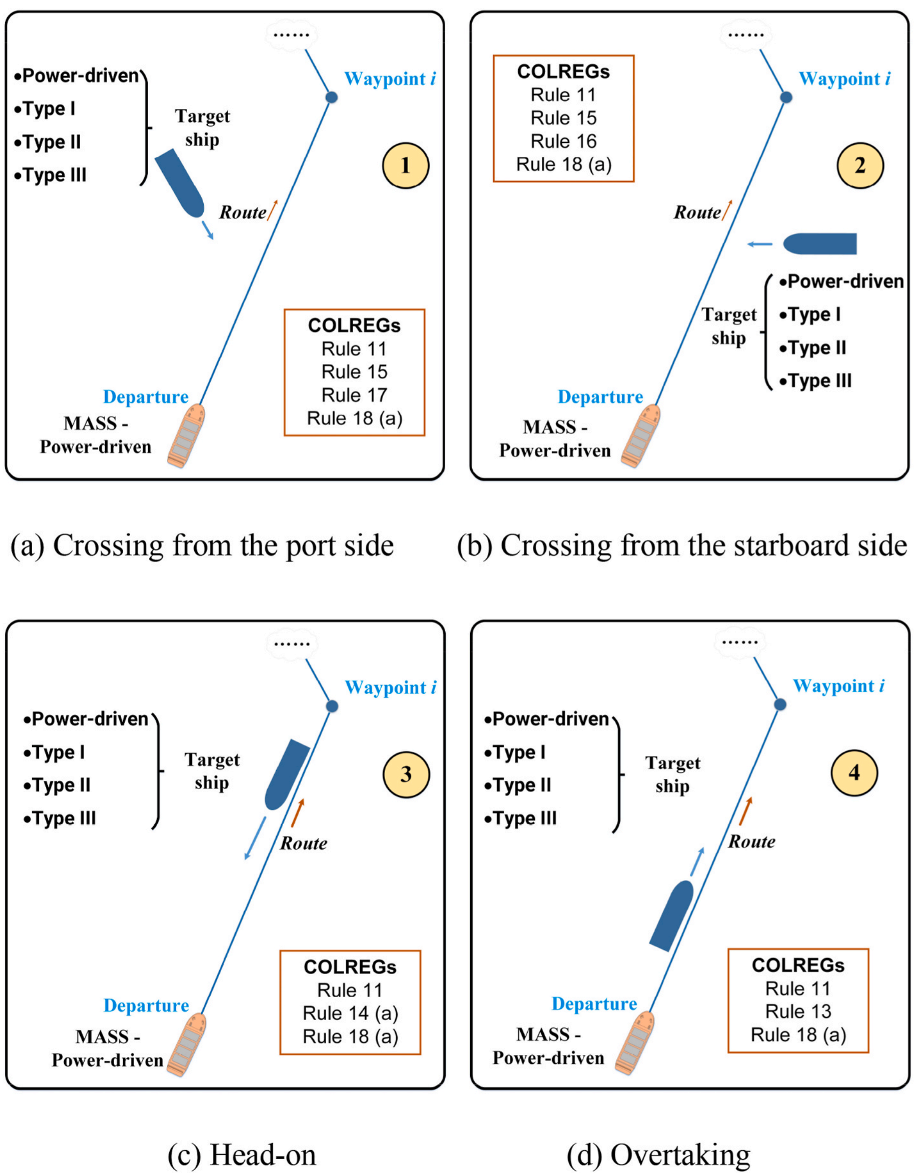


Fig. 6. The illustration of scenario setup for experimental verification.

Table 1
Overview of the motion characteristics of target ships.

No.	X_0	Y_0	V_x	V_y	Scenario
1	28	18	−0.4	−0.01	Crossing-starboard side
2	10	10	0.1	0.1	Overtaking
3	6	18	0.3	−0.3	Crossing-port side
4	30	30	−0.1	−0.1	Head-on

the weights γ, δ set to 1, causing the vessel to prioritise efficiency over safety. Additionally, the MASS maintained its heading rigidly with $\boldsymbol{\kappa}$ set to 1, hindering its ability to turn to avoid collisions. Therefore, γ, δ, $\boldsymbol{\kappa}$ were incrementally reduced from 1, while $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ remained at 1 for efficiency and safety. Through this iterative process, the weights were fine-tuned to $\boldsymbol{\alpha} = 1, \boldsymbol{\beta} = 1, \boldsymbol{\gamma} = 0.2, \boldsymbol{\delta} = 0.1, \boldsymbol{\kappa} = 0.01$. This adjustment set a baseline to ensure the MASS maintains its planned route while successfully avoiding collisions without considering COLREGs.

Subsequent fine-tuning focused on the parameter $\boldsymbol{\delta}$, which influences the rule adherence. To isolate the impact of η on the system's ability to conform to COLREGs, we conducted tests with its values varied across a discrete set: 0, 0.3, 0.6, and 1, while other parameters remained unchanged.

4. Experiment implementation

4.1. Simulation environment

The implementation and testing phase of this research established a simulation environment featuring the TU Delft-developed *Tito-Neri* model vessel (Haseltalab and Negenborn, 2019). This model simulates maritime dynamics, coexisting with target ships that maintain consistent behaviour across scenarios. An interface was designed for simulation, including three proximity levels using concentric circles: proactive avoidance marked in blue (5 times the length of the ship hull), defensive avoidance marked in green (3 times the length of the ship hull), and collision radius marked in red (the length of the ship hull). The details are shown in Fig. 5.

Moreover, the interface incorporates a situational understanding module in the middle of the right part of the interface, which invokes the designed knowledge maps ontology by calling Python's *owlready2* package for real-time reasoning. This module provides insights into the operational status of the MASS, including the algorithm currently in use, the vessel's mission objectives, and the navigation goal. In scenarios where the MASS encounters another vessel, the module delineates the type of the encounter, assigns roles as defined by the COLREGs, and stipulates the corresponding actions along with their timings.

In addition, different performance metrics of the DWA algorithm are shown in the interface, such as distance to target, obstacles, path keeping, etc. These metrics monitor the parameters of the KM-DWA algorithm.

The computational platform for these simulations was Python 3.10, running on an 11th Gen Intel(R) Core(TM) i7-1185G7 @ 3.00 GHz 1.80 GHz system.

4.2. Scenario-based testing

Testing was organised into the following scenarios.

1. Head-On: Assessing the system's course and speed adjustments as guided by COLREGs Rule 14.
2. Crossing: Evaluating the system's decision-making process in scenarios where target vessels approach from lateral directions, with a focus on varying ship types and manoeuvrability.
3. Overtaking: Testing the system's ability to safely and efficiently navigate overtaking manoeuvres in compliance with COLREGs Rule 13.

Specifically, the following experimental control variables were designed in the test scenario, including *manoeuvrability of the target vessel*, *traffic complexity*, and *the impact of COLREGs Compliance*. These variables are presented in detail in subsections 4.2.1 through 4.2.3 below.

4.2.1. The manoeuvrability of the target vessel

Target ship types categorised by COLREGs priorities include Power-driven vessels, Type I, Type II, and Type III. Specifically, their corresponding ship type or manoeuvrability is listed below.

- Type I: Sailing vessel;
- Type II: Engaged in fishing;
- Type III: Vessel constrained by her draught, Restricted in her ability to manoeuvre, and Vessel not under command

4.2.2. Traffic complexity

1. Individual Vessel Encounters: These scenarios examine the autonomous system's response to the individual vessel, testing its decision-making process and compliance with the applicable COLREGs rules.
2. Multi-Vessel Encounters: This scenario involves multiple vessels considering their manoeuvrability, which requires the MASS to make decisions considering multiple COLREGs rules simultaneously.

Fig. 6 illustrates four classic scenarios on which our algorithm will be tested to evaluate the system's performance and COLREG compliance. Table 1 offers an overview of target ships' motion characteristics in both individual and multi-vessel encounters.

4.2.3. The impact of COLREGs compliance

The algorithm's performance was tested under varying COLREGs compliance weights (0, 0.3, 0.6, 1) to assess how strict or flexible adherence impacts navigation efficiency and safety. This approach allows the evaluation of the KM-DWA algorithm.

5. Results and analysis

5.1. Performance metrics

This section outlines the performance outcomes from simulations designed to assess the integrated ontology-based knowledge maps with DWA for path-planning in MASS. The performance of the system was evaluated based on navigation safety, efficiency, and adherence to COLREGs.

To quantitatively evaluate the comprehensive performance of the algorithm, the following metrics were proposed.

- Safety Metrics: Whether or not there was a collision, the minimum DCPA, TCPA, and the minimum distances to be maintained from other vessels.
- Efficiency Metrics: Assessment of the path efficiency in terms of travel path length and travel time, as well as deviations from the optimal path.
- COLREGs Compliance: The distance at which the MASS begins to take proactive or defensive manoeuvres and whether the MASS complies with the rules for taking evasive actions in various scenarios, i.e., the consistency between the action recommended by the COLREGs and the action actually taken.

5.2. Performance evaluation

5.2.1. Encountering individual vessels

The simulation results for the DWA and KM-DWA algorithms across four scenarios—overtaking, head-on, crossing from starboard, and crossing from port—were analysed. In crossing with overtaking, head-

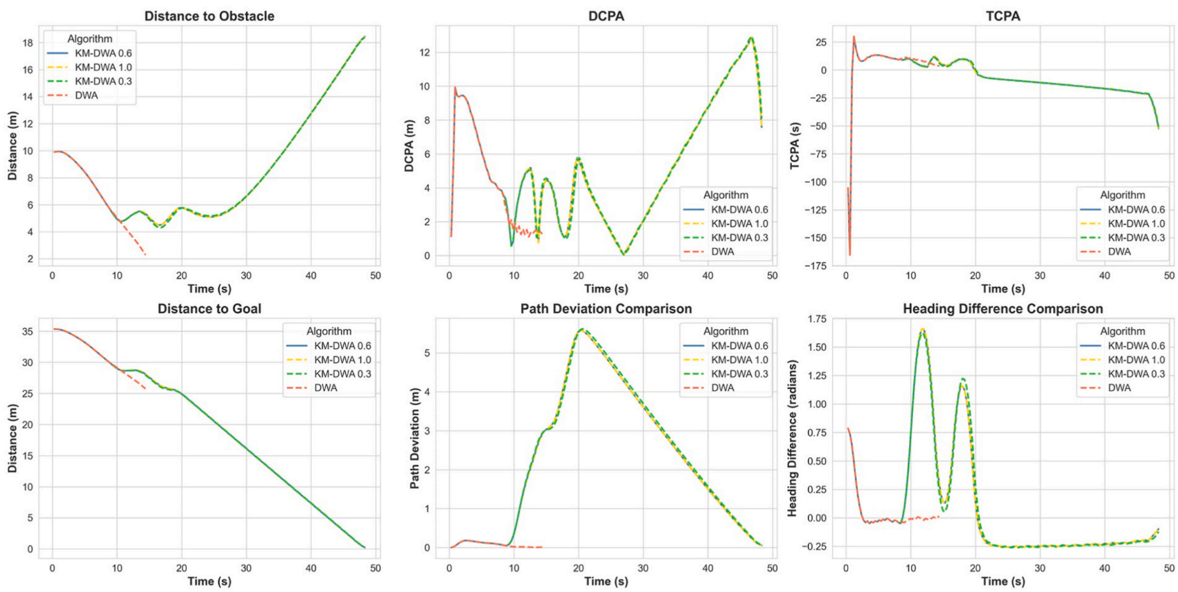


Fig. 7. Performance comparison when MASS is overtaking the target ship with manoeuvrability, including power-driven ship type, type I, type II, and type III.

on, and starboard side approaching vessel scenarios, the performance metrics were evaluated for target ships with power-driven capabilities, and those with restricted manoeuvring were classified as type I, II, and III. The performance curves are shown in Fig. 7, Figs. 10 and 11 (in Appendix), respectively, and it is found that the algorithmic performance data are the same for the same encounter type. Therefore, we first present here three figures that are representative of the performance of all target ship types in those encounter scenarios.

In the case of the vessel approaching on the port side, the execution of the algorithm differs significantly because COLREGs require different manoeuvring performances depending on the vessel's navigational priorities. Thus, two separate performance graphs were analysed: one where the target ship was a power-driven vessel, as shown in Fig. 13, and the other where the target ship's manoeuvring ability was classified as type I, II, or III, as shown in Fig. 12 (in Appendix).

More detailed analysis of the performance of algorithms in different scenarios are described below.

(1) **Overtaking Scenario**: The basic DWA algorithm collides with the target vessel in the overtaking scenario, as reflected by the broken red curves of the DWA algorithm in the subplots in Fig. 7 (Appendix). This indicates insufficient safety distances, according to the COLREGs, highlighting deficiencies in safety. Conversely, the other curves representing the KM-DWA variants avoid collisions altogether, reflecting a commitment to safety, with longer travel times as a trade-off.

(2) **Head-On Scenario**: For head-on encounters, the DWA algorithm continued to result in collisions, while KM-DWA variants perform collision-free navigation, reflected by the broken red curves of the DWA and other curves of KM-DWA variants in the subplots in Fig. 10 (in Appendix). As shown in the Heading Difference Comparison subplot of Fig. 10, the KM-DWA variants execute right-turn manoeuvres as required by COLREGs rules, leading to longer buffering distances, presented in the Distance to Obstacle, DCPA, and TCPA subplots, reducing collision risks and ensuring vessel's successful arrival at the destination, though resulting in a deviation from the optimal path (see Path Deviation Comparison

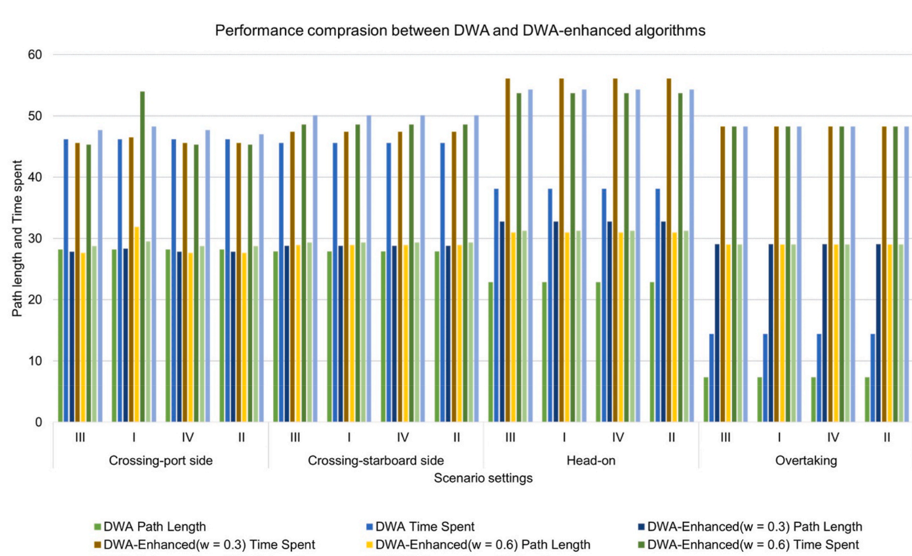


Fig. 8. The overall performance comparison between DWA and KM-DWA algorithms with different COLREGs weights.

subplot), signalling a strategic shift toward compliance with COLREGs over navigational efficiency.

(3) **Crossing Scenarios**: In scenarios involving crossing from the starboard and port sides, the KM-DWA variants adhered closely to COLREGs, initiating a right-turn manoeuvre for positive avoidance, unlike the DWA algorithm, which performed non-compliant left-turn actions in starboard crossing scenarios (see Heading Difference Comparison subplot of Fig. 11 (Appendix)). In port-side crossings, responses varied with the target vessel's type/manoeuvrability. When encountering power-driven vessels, the own vessel maintained its course and speed for a period as per rule 17 of COLREGs, beginning a right-turn manoeuvre only when the target entered a pre-set defensive avoidance distance. When the target vessel had inferior manoeuvrability, the own vessel took proactive right-turn manoeuvres to avoid the approaching vessel from the port side. Nevertheless, the DWA algorithm, while also successfully avoiding collisions, exhibited a gap in compliance (see Figs. 12 and 13)

(4) **Comparative Performance Analysis:**
- **Proximity to Obstacles**: While the DWA algorithm maintains closer, consistent proximity to obstacles, reflecting a reactive stance, the KM-DWA algorithms demonstrate an evolution towards proactive avoidance. The transition from reactive to proactive is gradual with increasing COLREGs weights, underscoring a strategy that deliberately favours safety over directness towards the goal.
- **Risk Assessment (DCPA and TCPA)**: The riskier navigational choices of the DWA are highlighted by its uniformly lower DCPA values. In contrast, the KM-DWA algorithms, particularly at higher COLREGs weights, reveal a trend of earlier and more decisive manoeuvres to increase the distance of the closest approach, signifying a preference for safety.
- **Navigational Path and Heading Adjustments**: The minimal path deviations and heading changes with the DWA suggest a preference for efficiency and direct routes. Conversely, the KM-DWA algorithms, especially with higher weights, accepted greater deviations and more significant heading adjustments to enhance collision avoidance and adherence to COLREGs.

(5) Weighted Performance of KM-DWA:
- **Low COLREGs Weight (0.3):** The algorithm began integrating COLREGs into decision-making, slightly increasing the distance to obstacles, indicating a proactive approach while maintaining a course relatively direct towards the goal.
- **Medium COLREGs Weight (0.6):** With a greater emphasis on safety, the vessel initiates avoidance of manoeuvres earlier, increasing path deviation and heading variation to ensure regulatory compliance, signalling a clear preference for safety over directness.
- **High COLREGs Weight (1.0):** At this setting, the algorithm exhibits a marked preference for safety, significantly altering the vessel's trajectory to avoid potential collisions. The substantial distance maintained from obstacles and the pronounced course corrections reflect the implementation of the principle of "early and broad" in COLREGs.

Additionally, the data representation shown in Fig. 8 provides a comprehensive overview of the algorithmic performances across various scenarios, illustrating distinct patterns in DWA and KM-DWA algorithms. The analysis of plotted metrics reveals that the KM-DWA algorithms consistently demonstrated longer trajectories than the basic DWA. This trend is evident in the cross-encounter scenarios (short paths in overtaking and head-on scenarios end early due to collisions), where basic DWA has shorter paths but can be more risky, as the 50% collision rate in these overtaking and head-on scenarios suggests. These findings underscore the potential risk of basic DWA, prioritising efficiency over safety.

Conversely, the KM-DWA variants result in longer durations, as they take more cautious routes to ensure full compliance with COLREG, as evidenced by the 100% compliance rate. This planning is evident in scenarios requiring right-crossing manoeuvres, where KM-DWA algorithms comply with COLREGs to avoid collisions, unlike the DWA, which made left-turn decisions that may lead to higher navigational risk, achieving only a 25% COLREGs compliance rate. These findings highlight the robustness of KM-DWA in safely navigating collision avoidance scenarios and explain the extended travel times and paths observed.

The experiments indicate that the KM-DWA algorithm adjusts its behaviour to accommodate these vessels' limited manoeuvrability, thus reinforcing a safety-first approach. Fundamentally, while the DWA algorithm prioritises path efficiency—reflected in shorter travel times and minimal deviations—it often fails to navigate safely across various scenarios. The improved safety measures of the KM-DWA algorithm, such as increased distances from obstacles and full compliance with COLREGs, are achieved through the acceptance of longer travel times and greater path deviations.

5.2.2. Encountering multiple vessels

Considering the good COLREGs compliance of the KM-DWA algorithm in single-vessel encounter scenarios, particularly with encountering power-driven vessels and target vessels with poor manoeuvrabilities, it is demonstrated that KM-DWA variants can account for the manoeuvrabilities of the target vessel during collision avoidance. Therefore, this section focuses on whether the variant algorithms are still capable of achieving COLREGs-compliant multi-vessel collision avoidance when considering target manoeuvreabilities and approaching vessels from multiple directions simultaneously.

For this purpose, we selected Type II as the manoeuvrability of target vessels, namely, engaged in fishing, in a multi-vessel encounter scenario to verify whether the MASS driven by the KM-DWA algorithm is able to accomplish autonomous safe collision avoidance in multi-vessel encounters. Fig. 9 visualises the collision avoidance trajectories of MASS driven by the DWA algorithm and KM-DWA variants with Type II target vessels. The whole process for collision avoidance of MASS is detailed below.

- **Initial Encounter (Port side crossing with TS1):** As shown in Fig. 9, KM-DWA variants demonstrate an early initiation of avoidance manoeuvres compared to the basic DWA algorithm, indicating a proactive approach to collision avoidance. KM-DWA variants differ from the basic DWA algorithm in the timing of manoeuvres for the initial encounter (port side crossing) with the target vessel TS1. KM-DWA algorithms initiate the proactive avoidance manoeuvre earlier than the DWA algorithm and take action at the proactive avoidance distance. This indicates that the KM-DWA variant algorithm accounts for the manoeuvrability of the target vessel and takes proactive actions, while the DWA algorithm ignores this situation.
- **Subsequent Course Adjustments**: Subsequently, KM-DWA employs a course adjustment to avoid collision as it passes the target vessel TS4, which is informed by a comprehensive evaluation based on criteria including collision avoidance, DCPA, and TCPA metrics. After the adjustment, the KM-DWA algorithm encounters another vessel, the TS2, on its starboard side, necessitating a moderate starboard turn in line with proactive collision avoidance strategies. This action ensures compliance with situational requirements and avoids excessive path deviation. The algorithm then corrects its heading to pass the target vessel safely, the TS3, subsequently resuming its original course towards the destination. These actions adhere to regulations for head-on encounters, including executing a starboard turn to mitigate collision risk. Upon clearing potential collision threats, the vessel returns to a standard navigational state and reaches its destination, guided by various cost functions.
- **DWA algorithm**: In contrast, the trajectory governed by the DWA algorithm exhibits fewer course adjustments, lacking the secondary

manoeuvres evident in the KM-DWA's initial and subsequent encounters. While remaining regulatory compliant, the DWA algorithm maintains closer proximity to the target vessel, increasing navigation risk.

Fig. 14 (Appendix) demonstrates the performance of the DWA algorithm and the KM-DWA variants in accomplishing collision avoidance in the same multi-ship encounter scenario, which is analysed as follows.

(1) Distance to Obstacle and Goal
- **DWA**: Demonstrates a consistent but risk-tolerant navigational approach towards obstacles, e.g., lower DCPA and TCPA, and disregard when the target vessel's poor manoeuvrability, showing a tendency towards efficiency over safety.
- **KM-DWA 0.3**: Begins to integrate a proactive collision avoidance strategy, showing a slight increase in the distance to obstacles while still maintaining efficiency.
- **KM-DWA 0.6 and 1.0**: These settings result in a marked increase in the distance to obstacles, indicating a strong preference for safety. The performance curves for these two weights overlap, suggesting that beyond a certain threshold, increasing the weight assigned to COLREGs compliance does not significantly alter the behaviour of the algorithm under the tested conditions.

(2) DCPA and TCPA
- **DWA**: Lower DCPA values indicate a riskier, closer approach to obstacles.
- **KM-DWA 0.3**: Shows improved safety margins with slightly higher DCPA values.
- **KM-DWA 0.6 and 1.0**: Both exhibit higher DCPA values, with a significant emphasis on safety and compliance, as reflected by the early transition of TCPA from positive to negative. The similarity in their performance curves suggests that both settings prioritise safety to a similar extent.

(3) Path Deviation and Heading Difference
- **DWA**: Minimal path deviation and heading variation indicate a straightforward but less cautious approach.
- **KM-DWA 0.3**: Increased path deviation and heading changes indicate a shift towards a more safety-compliant navigation strategy.
- **KM-DWA 0.6 and 1.0**: Display the highest path deviations and heading changes, showcasing adherence to proactive collision avoidance. The convergence of their performance curves indicates a shared strategy for safety, suggesting a plateau in the enhancement of safety measures when the COLREGs weight is increased beyond 0.6 under the tested scenarios.

The above findings emphasise the need for an algorithmic balance between efficiency, safety, and regulatory compliance. The system effectively integrated data from the knowledge maps with the DWA in multi-vessel scenarios, demonstrating.

1) **Decision Making in Complex Scenarios**: The MASS successfully navigated complex multi-vessel encounters by prioritising actions based on safety and COLREGs compliance.
2) **Conflict Resolution**: In situations with rule conflicts, the system demonstrated a high capability to resolve conflicts and choose the safest navigational action.
3) **Proximity to Obstacles**: The KM-DWA algorithms, particularly with higher COLREGs weights, consistently maintain safer distances from obstacles, suggesting a prioritisation of collision avoidance over route directness.
4) **Navigational Timelines**: Correspondingly, the KM-DWA algorithms exhibit prolonged travel times, likely a reflection of their circuitous routes to ensure compliance with maritime rules.

6. Discussion

This study critically evaluates DWA against its ontology-integrated enhancement within the domain of MASS navigation. By embedding a knowledge maps model, the resulting KM-DWA algorithm aims to augment path planning with increased safety, efficiency, and regulatory compliance. Compared to other previous studies, the KM-DWA algorithm demonstrates its capability to avoid collisions while complying with COLREGs in both individual vessel and multi-vessel encounter scenarios.

The trade-off between safety and efficiency: A trade-off between safety and efficiency is evident. As the weight of rule compliance increases, the safety level of a vessel increases while its efficiency decreases relatively, and vice versa. Therefore, it is necessary for MASS to set the weight flexibly to achieve a balance between safety and efficiency in real navigation.

Comparison with existing studies: In this study, we build upon the previous studies, such as (Song et al., 2022), (Thombre et al., 2022), and (Zhang et al., 2021), which highlighted the importance of situational awareness in MASS navigation. We extend the previous work (Song et al., 2022) by constructing structured knowledge maps for MASS navigation that continuously update the situational information with real-time navigational and environmental data, thereby enhancing situational awareness. Additionally, our study broadens the interpretation of COLREGs by extending the scope of earlier studies by (Zhang et al., 2022) and (Lee and Kwon, 2004) to include a broader range of rules, scenarios, and proactive collision avoidance strategies. We also adapt the DWA algorithm for a 3-DOF MASS model, originally proposed for robotics by (Fox et al., 1997) and further applied in the maritime domain by (Brock and Khatib, 1999). By integrating it with our knowledge maps model and extended COLREGs interpretation mechanism, we enhance its capability of scenario recognition and COLREGs compliance.

3-tier collision avoidance distance: The implementation of this concept provides a positive and rule-compliant approach to avoid collisions. The three tiers serve as triggers for initiating collision avoidance manoeuvers, with specific distances set for different roles under COLREGs. The study proves that vessels correctly trigger different avoidance distances based on their role—defensive avoidance distance when acting as the stand-on vessel and active avoidance distance when acting as the give-way vessel. This mechanism assists vessels in integrating COLREGs into their collision avoidance behaviour to clarify their intentions to manned ships.

Encountering with target ships: In individual vessel encounters, the basic DWA tends to prioritise direct routes, potentially compromising safety margins and COLREGs adherence. In contrast, the KM-DWA algorithm variants demonstrate a commitment to safety and regulatory compliance, even if it means accepting longer travel times and paths. Simulations for MASS with Type II target vessels in multi-vessel encounter scenarios demonstrate that KM-DWA algorithms adapt their behaviour to accommodate the constrained manoeuvrability of these vessels (i.e., Type I, Type II, and Type III), reinforcing the safety-first approach. In essence, while the basic DWA algorithm prioritises path efficiency, reflected in shorter travel times and minimal deviation, it frequently fails to navigate safely across various scenarios. The KM-DWA algorithm's safety measures, such as increased distances to obstacles and full compliance with COLREGs, are achieved by accepting a trade-off in the form of longer travel and greater path deviations.

Future advancement: Future research should aim to refine the balance between safety and efficiency, possibly by employing machine learning strategies to navigate complex scenarios optimally. Expanding the test cases to a broader spectrum of environmental contexts could provide a more rounded evaluation of the algorithms' capabilities. Incorporating real-time data analytics to dynamically adjust COLREGs weightings within the KM-DWA could further enhance the safety and efficiency of navigation.

In summary, the KM-DWA algorithm maintains safety and navigational efficiency while complying with COLREGs, suggesting its potential for operational development in autonomous navigation. Its adaptability, allowing for flexible weight configurations to balance efficiency, safety, and rule compliance, is crucial. The 3-tier collision avoidance distance strategy further ensures that vessels can integrate COLREGs effectively, enhancing both proactive and defensive collision avoidance.

7. Conclusion and future directions

This study highlights the value of integrating an ontology-based knowledge maps model with DWA to enhance the navigational decision-making of MASS. The research has demonstrated, through simulation, the potential of this integration to uphold situational awareness, such as COLREGs understanding and compliance, in complex scenarios, suggesting a promising direction for future maritime autonomous navigation.

Key contributions include a COLREGs enhanced knowledge-map-based situational awareness model, a tailored adaptation of the DWA for maritime contexts, and innovative proactive and defensive collision avoidance by integrating the advantages of DWA and COLREGs, thereby achieving a preliminary MASS with situational awareness, which does not just defensively avoid collisions. While these contributions mark a step towards more autonomous maritime systems, the research's simulations will need to be tested in the real world, especially when interacting with conventional manned vessels and the effects of hydrodynamic factors.

Nevertheless, there are several limitations that must be acknowledged. Firstly, the research primarily relies on simulation results, which may not fully capture the complexities of the navigational environment, including sea status and the regulation of the local area. Secondly, this study did not consider interactions between vessels, which is critical for collision avoidance as it is a real-time interactive process. Considering the navigational preferences of vessels is essential for ensuring safe, efficient, and seafarer-friendly collision avoidance. The framework's applicability to different types of vessels and their specific operational characteristics was not thoroughly explored, necessitating further investigation.

Thus, future research should aim at the following points.

1. Expand the knowledge maps and integrate other laws and regulations to facilitate improved operator understanding and interaction with the autonomous system, strengthening the trust in and reliability of autonomous navigational decisions.
2. Validate the simulated results through real-world trials to ensure the system's robustness in the diverse conditions encountered in maritime environments.
3. Customise the system for varied vessel types, ensuring that specific operational characteristics are factored into navigational decisions.
4. For manned ships with different navigation preferences, the system can improved with intelligent navigation decisions that take the human driver's navigation preferences into consideration.

In sum, while acknowledging the limitations of simulation-based findings, this research provides a foundational step towards the realisation of safe, efficient, and intelligent navigational systems for MASS. It is anticipated that the avenues outlined for future work will further validate the current findings and expand the operational capabilities of autonomous maritime vessels.

CRediT authorship contribution statement

Rongxin Song: Writing – original draft, Validation, Software, Methodology, Conceptualization. **Eleonora Papadimitriou:** Writing – review & editing, Supervision, Conceptualization. **Rudy R. Negenborn:** Writing – review & editing, Supervision, Resources, Conceptualization. **Pieter van Gelder:** Writing – review & editing, Supervision, Resources, Project administration, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Rongxin Song reports financial support was provided by China Scholarship Council. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

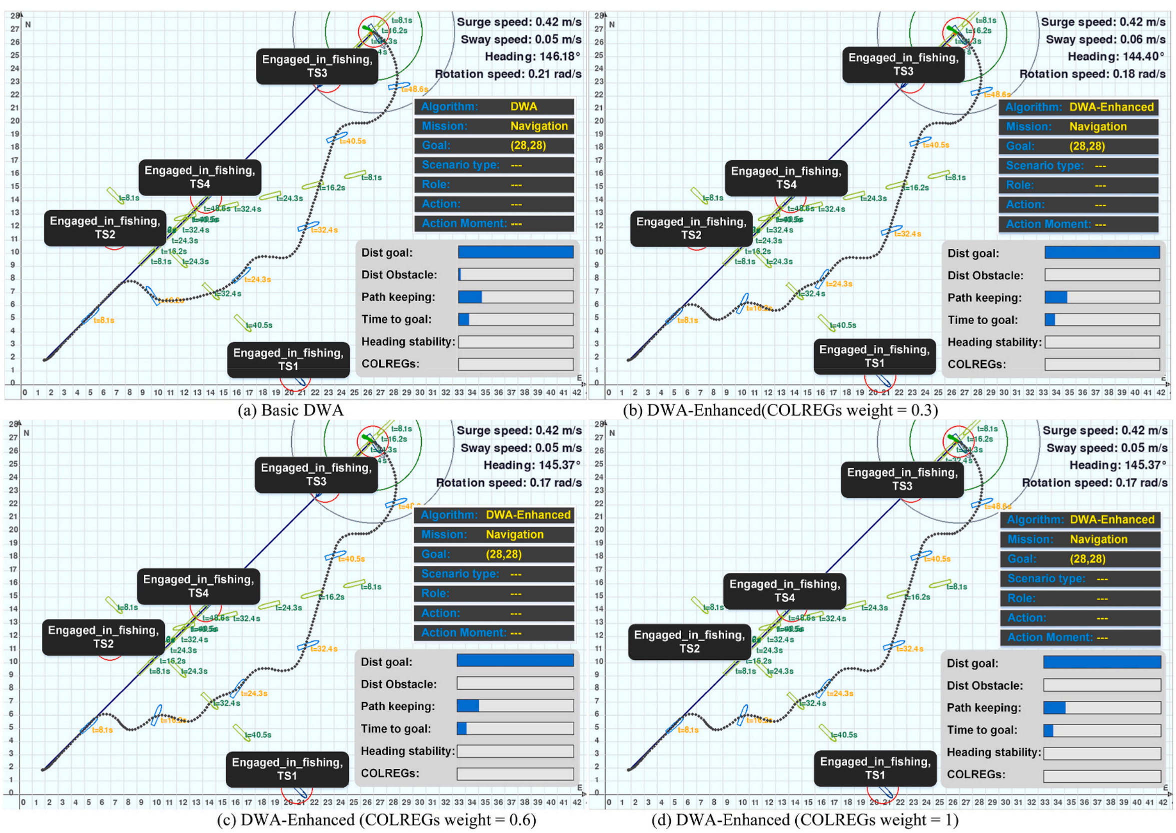
Table 2
Translation of Maritime Collision Regulations into SWRL Rules

COLREGs	Description	SWRL Translation
Rule 11	Application: in sight of one another	MASS(?s1) ^ Target_ships (?s2) ^ involve_risk_of_collision (?s1, ?s2) ^ Scenario (?ss) ^ encounter_scenario (?s1, ?ss) ^ encounter_scenario (?s2, ?ss) ^ has_visibility (?ss, in_Sight_of_One_Another) - > should_obey_regulation (?s1, Rule11) ^ should_obey_regulation (?s2, Rule11)
Rule 13	Overtaking	Scenario (?ss) ^ encounter_scenario (?s1, ?ss) ^ Target_ships (?s2) ^ involve_risk_of_collision (?s1, ?s2) ^ encounter_scenario (?s2, ?ss) ^ has_visibility (?ss, in_Sight_of_One_Another) ^ in_overtaking (?s1, ?s2) ^ MASS(?s1) - > should_obey_regulation (?s1, Rule11) ^ hasCArole (?s1, give_way) ^ should_obey_regulation (?s1, Rule14) ^ should_give_way (?s1, ?s2)
Rule 14	Head-on situation	Scenario (?ss) ^ encounter_scenario (?s1, ?ss) ^ Target_ships (?s2) ^ involve_risk_of_collision (?s1, ?s2) ^ encounter_scenario (?s2, ?ss) ^ has_visibility (?ss, in_Sight_of_One_Another) ^ in_head_on (?s1, ?s2) ^ MASS(?s1) - > should_obey_regulation (?s1, Rule11) ^ hasCArole (?s1, give_way) ^ should_obey_regulation (?s1, Rule14) ^ should_take_action (?s1, turn_to_starboard_side)
Rule 15	Crossing situation	Scenario (?ss) ^ encounter_scenario (?s1, ?ss) ^ Target_ships (?s2) ^ involve_risk_of_collision (?s1, ?s2) ^ encounter_scenario (?s2, ?ss) ^ has_visibility (?ss, in_Sight_of_One_Another) ^ in_crossing (?s1, ?s2) ^

(*continued on next page*)

Table 2 (*continued*)

COLREGs	Description	SWRL Translation
		MASS(?s1) - > should_obey_regulation (?s1, Rule11) ˆ hasCArole (?s1, should_give_way) ˆ should_obey_regulation (?s1, Rule15) ˆ should_take_action (?s1, turn_to_starboard_side)
Rule 16	Action by give-way vessel	hasCArole (?s1, give_way) ˆ MASS(?s1) - > should_obey_regulation (?s1, Rule16) ˆ shouldCAmoment (?s1, Early_proactive)
Rule 17(a) (i)	Stand-on vessel maintaining course and speed	hasCArole (?s2, give_way) ˆ hasCArole (?s1, stand_on) ˆ Target_ships (?s2) ˆ MASS(?s1) - > should_obey_regulation (?s1, Rule17) ˆ should_take_action (?s1, keep_course_and_speed) ˆ shouldCAmoment (?s1, Early_proactive)
Rule 17(a) (ii) & Rule 17(b)-Rule 17(d)	Stand-on vessel taking action to avoid collision by her manoeuvre alone.	hasCArole (?s2, give_way) ˆ hasCArole (?s1, stand_on) ˆ Target_ships (?s2) ˆ MASS(?s1) ˆ performingBehavior (?s2, keep_course_and_speed) - > should_obey_regulation (?s1, Rule17) ˆ should_take_action (?s1, turn_to_starboard_side) ˆ shouldCAmoment (?s1, Imminent_defensive)
Rule 18-(a)	Power-driven vessel giving way to vessels with restricted manoeuvrability	Target_ships (?s2) ˆ has_shiptype (?s1, powerdriven_vessel) ˆ has_shiptype (?s2, ?t) ˆ I_type (?t) ˆ MASS(?s1) - > hasCArole (?s1, give_way) ˆ should_obey_regulation (?s1, Rule18) ˆ should_take_action (?s1, keep_out_of_the_way) ˆ shouldCAmoment (?s1, Early_proactive) ˆ should_give_way (?s1, ?s2)
Rule 18-(b)	Sailing vessel giving way under certain conditions	Target_ships (?s2) ˆ II_type (?t) ˆ has_shiptype (?s2, ?t) ˆ MASS(?s1) ˆ has_shiptype (?s1, sailing_vessel) - > hasCArole (?s1, give_way) ˆ should_obey_regulation (?s1, Rule18) ˆ should_take_action (?s1, keep_out_of_the_way) ˆ shouldCAmoment (?s1, Early_proactive) ˆ should_give_way (?s1, ?s2)
Rule 18-(c)	Vessel engaged in fishing maintaining course and speed.	Target_ships (?s2) ˆ has_shiptype (?s2, ?t) ˆ has_shiptype (?s1, engaged_in_fishing) ˆ MASS(?s1) ˆ III_type (?t) - > hasCArole (?s1, give_way) ˆ should_obey_regulation (?s1, Rule18) ˆ should_take_action (?s1, keep_out_of_the_way) ˆ shouldCAmoment (?s1, Early_proactive) ˆ should_give_way (?s1, ?s2)



(a) Basic DWA (b) DWA-Enhanced(COLREGs weight = 0.3)

(c) DWA-Enhanced (COLREGs weight = 0.6) (d) DWA-Enhanced (COLREGs weight = 1)

Fig. 9. Visualisation of the collision avoidance trajectories of MASS with different COLREGs weights in the case of multi-ship encounters.

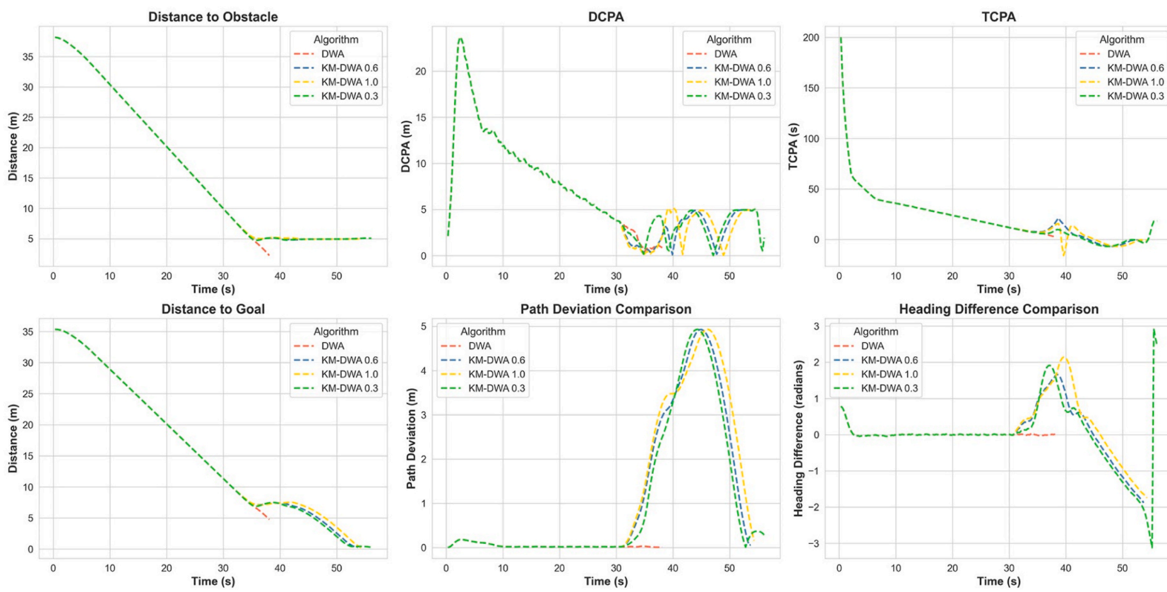


Fig. 10. Performance comparison when MASS encounters the target ship with manoeuvrability, including power-driven ship type, type I, type II, and type III and forming the head-on situation

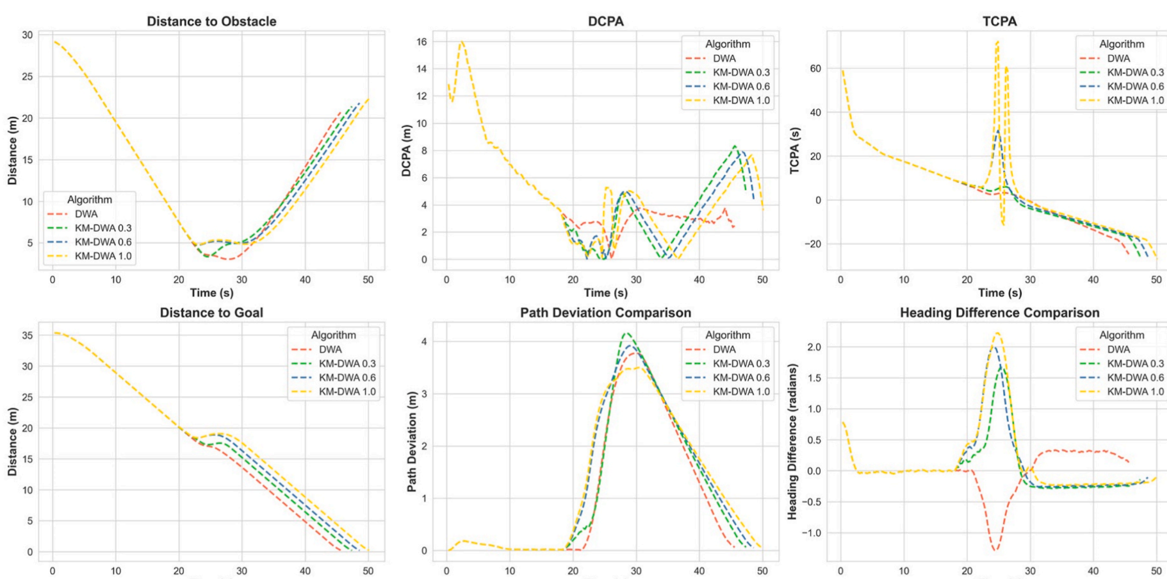


Fig. 11. Performance comparison when MASS encounters the target ship with manoeuvrability, including power-driven ship type, type I, type II, and type III approaching from the starboard side

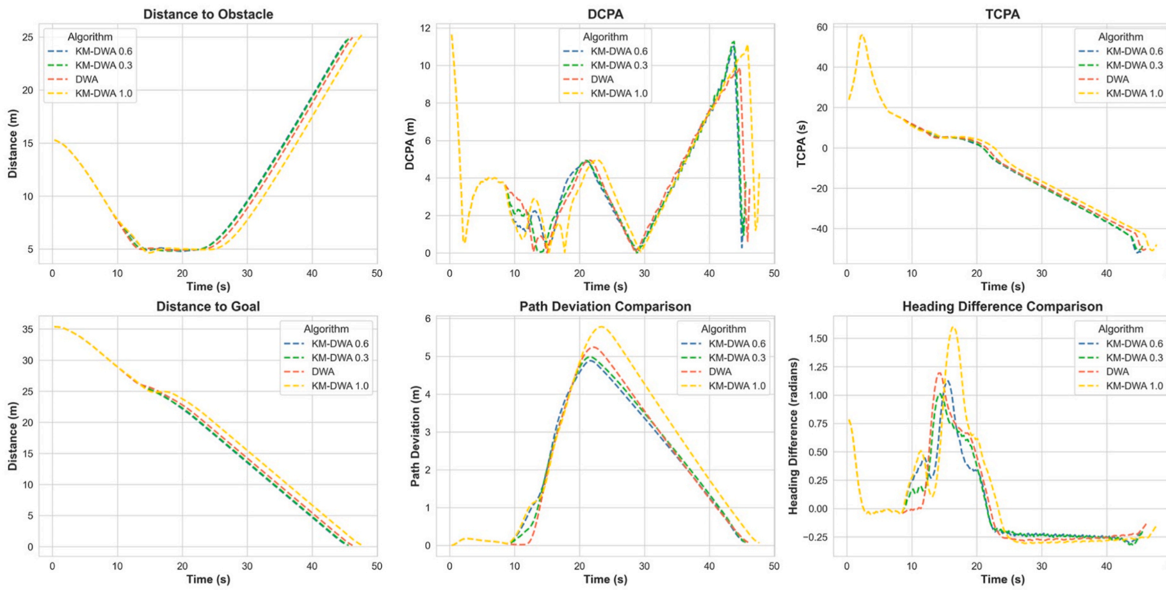


Fig. 12. Performance comparison when MASS encounters the target ship with manoeuvrability, including type I, type II, and type III approaching from the port side

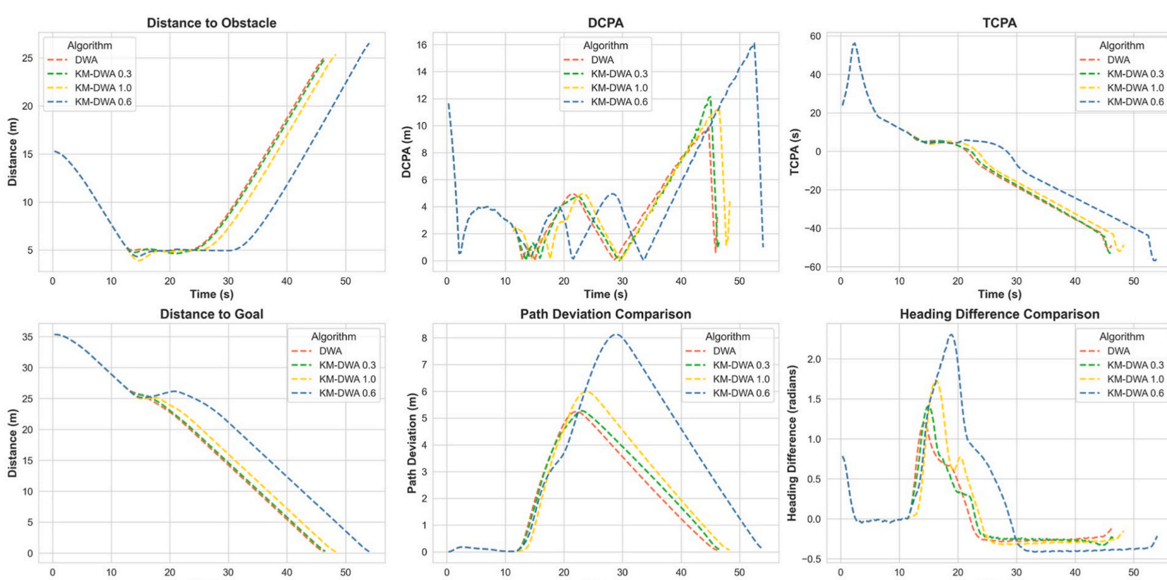


Fig. 13. Performance comparison when MASS encounters the target ship with the ship type of power-driven approaching from the port side

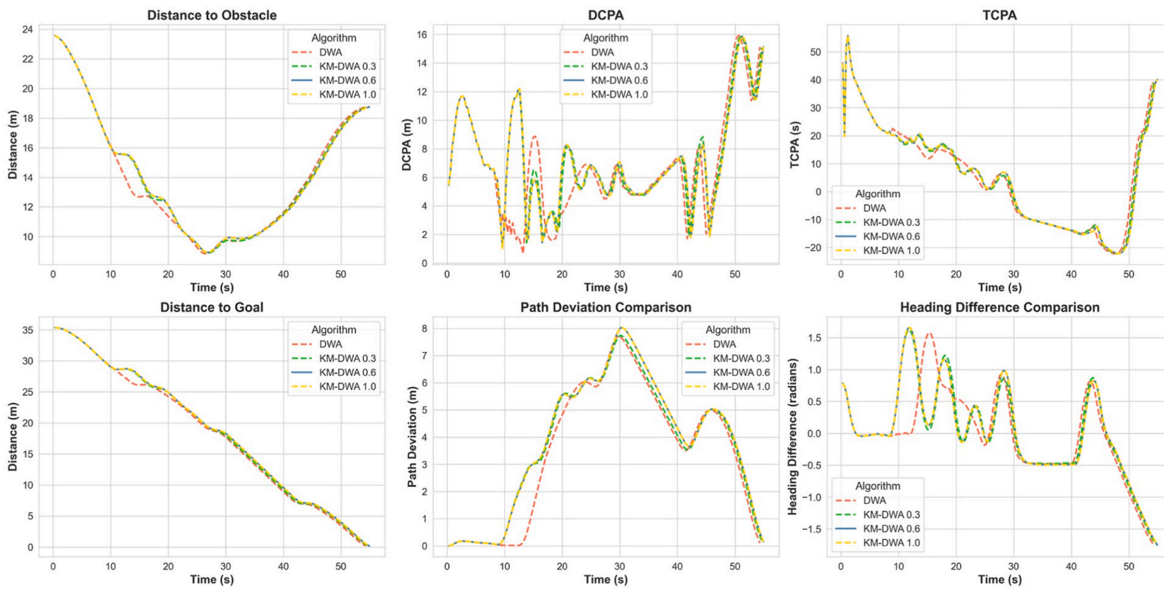


Fig. 14. Performance comparison between different algorithms in the multi-vessel encounter scenario

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