



TRA VISIONS 2024

Final Project Template – This template is to be used for submitting the final version of the project. The final deliverable should be submitted by the 31st of October 2023

Idea Number:

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PILLAR / TRANSPORT MODE				
ROAD ☐	RAIL ☐	WATERBORNE ☒	AIRBORNE ☐	CROSS MODAL ☐
Project Related to:	☐ RA1: Safe & Inclusive Transport ☐ RA2: Sustainable Mobility of People & Goods ☒ RA3: Collaborative Digitalisation ☐ RA4: Efficient & Resilient Systems			

Project Title:

ROBUST REACTIVE COLLISION AVOIDANCE SYSTEM FOR AUTONOMOUS SHIPS
AMIDST LIMITED SENSORY INFORMATION AND UNCLASSIFIED SURFACE
OBSTACLES



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MANAGEMENT SUMMARY

The recent maritime industry has been transitioning to the new era of Shipping 4.0 propelled by the vision of a more sustainable future. Autonomous ships, also known as Maritime Autonomous Surface Ships (MASSs), are envisioned to be the main ecosystems of Cyber-Physical Systems (CPSs) with the potential to unlock new levels of sustainability. However, prior to their full-scale adoption, new challenges pertaining to safety-critical operations need to be addressed, such as collision avoidance. In particular, ensuring safe and efficient collision avoidance of MASSs under uncertainties is an ever-increasing key challenge. To tackle this, a novel idea is proposed to develop a reactive collision avoidance system for MASS with robust decision-making and scenario-classification capabilities amidst limited sensory information and unclassified surface obstacles. This idea is formulated into a systematic methodology that consists of the development of a high-fidelity digital twin environment, development and training of Artificial Intelligence (AI)-based agents for decision-making and scenario-classification, and verification of the system's robustness. Simulation results verify that the decision-making agent can generate efficient, safe, and CORLEGS-compliant evasive manoeuvres even outside of the training envelope. Also, the scenario-classification agent can identify a static or dynamic scenario with accuracy above 82.8%. Finally, the developed system can handle reactive collision avoidance amidst a wide range of unclassified obstacles resembling surface obstacles with radii of 4-470 m and target vessels ranging from 12-104 m in length. This idea contributes to the future of sustainable maritime industry by paving the way for robust autonomous systems in safety-critical applications.

The contents are as follows. Section 1 presents the background information of the proposed idea. Section 2 describes the research area of the main challenge being tackled. Section 3 provides a literature review of the pertinent studies. Section 4 outlines the novel contributions of the idea and its methodology. Section 5 describes the main design characteristics of the methodology. Section 6 presents the derived results with discussions. Finally, Section 7 finishes with concluding remarks, identified technology gaps, and outlook for future work.

1. INTRODUCTION

Maritime shipping is the backbone of world's trade and globalisation [1]. Over 80% of international trade's volume and 70% of its value are waterborne [2], as it is by far the most dependable, efficient, and cost-effective mode of transportation [3]. It has an indisputable strategic position to improve people's life quality by providing access to essential commodities, such as food and energy, reduce environmental impact by enhancing fuel efficiency per t-km freight services, and stimulate economic growth by enabling cross-border trade liberalisation between developed and developing countries [4]. Thus, maritime shipping is considered to be one of the lifelines to realise global sustainability based on the Sustainable Development Goals set by the United Nations [5].

Since the early 2010s, the vision for a more sustainable future propelled by the paradigm of Industry 4.0 has paved the way towards the transition of the traditional maritime shipping to the new Shipping 4.0 era [6]. Shipping 4.0 describes the fully interconnected maritime ecosystem characterised by the increased digitalisation via Key Enabling Technologies (KETs), such as Internet of Things, Cloud Computing, Big Data Analytics, Virtual and Augmented Reality, Cyber-Security, Additive Manufacturing, and Artificial Intelligence (AI) [7]. The leverage of such KETs is envisioned to create an ecosystem of CPSs that link their physical entities to the digital world with locally embedded intelligence to unlock new levels of sustainability through more efficient and effective communication, monitoring, decision-making, and control in a decentralised and distributed manner [8].

The main building blocks that encompass such ecosystems of CPSs are the autonomous ships [7], also known as Maritime Autonomous Surface Ships (MASSs). Depending on the degree of autonomy, a MASS can adopt increased computerised and monitoring systems with remotely controlled and automated capabilities to onboard intelligent systems with decision-making capabilities [9]. At the highest degree of autonomy more responsibilities are expected to be transferred to intelligent decision-making systems that can operate independently of human interaction [10]. However, this inevitably leads to the introduction of new challenges pertaining to safety-critical operations and amongst them collision avoidance is deemed to be one of the most challenging ones [11].

2. RESEARCH AREA

The nature of ship collision avoidance is a demanding endeavour with intrinsic multifaceted challenges [12]. Particularly, it requires the control of a large underactuated vessel in an unstable sea medium [13], which can be further exacerbated amidst adverse weather conditions, complex traffic scenarios, and current trend towards increased world fleet's number and sizes [8]. Also, global maritime accident statistics suggest that collision is the leading accident category constituting as much as 64% of all accidents from 2001 to 2020 [14]. The aftermath of collision accidents is catastrophic in terms of human life loss, environmental pollution, and financial damage [15], such as the collision of the Sanchi oil tanker in 2018 that resulted in the life loss of all 32 crew members, 138,000 t of oil leakage into the ocean, and \$100 million loss [16].

Although, it is hard to predict what the consequences of such accidents will be in the autonomous spectrum, the emergence of new challenges due to the adoption of MASSs is certain [17]. For instance, despite human error constituting as much as 94.7% of all collision accidents [18], human contribution to accident mitigation, though not reported, cannot be underestimated and how intelligent decision-making systems will react in similar situations is questionable [19]. Moreover, the ability of those systems to comprehend and mimic ambiguous human behaviours, such as good seamanship, remains open [20]. Finally, the scepticism towards ethical and safety related issues and the general outline of the International Regulations for Preventing Collisions at Sea (COLREGs) render the public acceptance for the safe coexistence of conventional ships and MASSs highly debatable [21].

To tackle these challenges and set new milestones in safer and more efficient future maritime scene, there has been a growing body of research that investigates the development of collision avoidance systems for MASSs. Collision avoidance is a subfield of path planning and deals with the guidance of the vessel from its original location to the final goal with safety being the most fundamental objective [22]. Recently, more research has focused on reactive collision avoidance, which refers to real-time evasive manoeuvres based on onboard sensory information, as it is the defining factor of its degree of autonomy for real-world applications, where information acquisition is typically incomplete, uncertain, and dynamically altered by external disturbances and locally detected obstacles [23].

3. LITERATURE SURVEY

Methods used for reactive collision avoidance can be classified into classical, heuristic, Deep Reinforcement Learning (DRL), or hybrid approaches [24], as presented in Table 1. Classical methods follow rigid procedures to provide an optimal solution, but their effectiveness highly depends on the completeness of the information that cannot always be guaranteed in real-world scenarios [25]. Commonly used methods are the A star (A*) [26], Velocity Obstacle (VO) [27], Artificial Potential Field (APF) [28], and Model Predictive Control (MPC) [29]. Heuristic methods rely on soft computing techniques to obtain near-optimal solutions, but their failure to always provide a solution and their high computation have been the main barriers [30]. Commonly used methods are the Fuzzy Logic (FL) [30], Genetic Algorithm (GA) [31], Particle Swarm Optimisation (PSO) [25], Beetle Swarm Antenna Search (BSAS) [32].

More recently, DRL methods have gained significant attention due to their major breakthroughs in addressing complex decision-making problems of high-dimensional spaces with significant end-to-end learning at a human-level [33]. Particularly, their success relies on the decision-making capabilities of Reinforcement Learning through the trial-and-error approach and the feature extraction capabilities of Deep Learning (DL) through the utilisation of Artificial Neural Networks (ANNs) [34]. Commonly used methods are the Deep Q-Network (DQN) [35], Soft Actor-Critic (SAC) [36], DDPG [37], Proximal Policy Optimisation (PPO) [38], and Twin Delayed DDPG (TD3) [39].

To realise robust reactive collision avoidance, pertinent studies have considered plethora of decision-making parameters. For virtual manoeuvring simulations, different ship dynamics have been used, such as Abkowitz [30], Nomoto [35], and Manoeuvring Modelling Group (MMG) [32]. To increase the fidelity of simulations, environmental disturbances have been considered, such as current, wind, and wave [28]. Collision risk has been quantified using various indicators, known as Collision Risk Indexes (CRIs), such as ship domain, distance, angle, Distance and Time to Closest Point of Approach (DCPA, TCPA) [33]. Multiple dynamic and static obstacles and COLREGs scenarios from single to multiple target ships have been investigated [26]. Most studies considered ideal measurements for obstacle detection and only some considered sensor measurements, such as using a LiDAR [36]. Summary of the pertinent literature is presented Table 2.

Table 1 Summary of the used methods. The heatmap represents the following: ‘●’ for ‘good’, ‘●’ for ‘mediocre’, and ‘●’ for ‘bad’.

Methods	Optimal solution	Real-time application	Path smoothness	Dynamic environment	Generalisation capabilities	Ease of use
A*	●	●	●	●	●	●
VO	●	●	●	●	●	●
APF	●	●	●	●	●	●
MPC	●	●	●	●	●	●
FL	●	●	●	●	●	●
GA	●	●	●	●	●	●
PSO	●	●	●	●	●	●
BSAS	●	●	●	●	●	●
DQN	●	●	●	●	●	●
SAC	●	●	●	●	●	●
DDPG	●	●	●	●	●	●
PPO	●	●	●	●	●	●
TD3	●	●	●	●	●	●

Table 2 Summary of the pertinent literature review.

Pertinent study	Ship dynamic	Environmental disturbances	Obstacle category	Obstacle detection	Obstacle classification	CRIs	COLREGs
[26]	-	Current	Static Dynamic	Ideal	Ideal	Ship domain	Y
[27]	3 DOF	-	Dynamic	Ideal	Ideal	DCPA TCPA	Y
[28]	3 DOF	Current Wind Wave	Static	LiDAR	Ideal	-	-
[40]	-	Water level	Static	Infrared camera	Ideal	Ship domain	-
[29]	3 DOF	Current Wind Wave	Dynamic	Ideal	Ideal	-	Y
[30]	Abkowitz 3 DOF	-	Dynamic	Ideal	Ideal	DCPA TCPA	Y
[31]	-	-	Dynamic	Ideal	Ideal	Ship domain DCPA	Y
[25]	-	Current	Static Dynamic	Ideal	Ideal	Ship domain	Y
[32]	MMG 3 DOF	-	Dynamic	Ideal	Ideal	Ship domain DCPA TCPA Distance Angle	Y
[35]	Nomoto 3 DOF	-	Static Dynamic	Ideal	Ideal	Ship domain	Y
[36]	3 DOF	-	Static Dynamic	Ideal	Ideal	Distance	Y
[37]	3 DOF	-	Static	Ideal	Ideal	Distance	-
[38]	1 st order Nomoto	-	Static Dynamic	Ideal	Ideal	Distance	Y
[39]	-	-	Static Dynamic	Ideal	Ideal	Distance	-

4. PROPOSED IDEA

4.1. NOVEL CONTRIBUTION

Review of the pertinent literature suggests that further research on reactive collision avoidance based on limited sensory information is needed. Particularly, most studies consider the ideal scenario where information of a static or dynamic obstacle is fully known, such as its location and size, from an Electronic Chart Display and Information System (ECDIS) or an Automatic Identification System (AIS), respectively. However, ECDIS data relies on a predefined static map that is hard to be updated in real-time [41]. Also, AIS data relies on active data transmission between all encountering ships that can be delayed from every 2 up to 180 seconds and even fail to transmit in case of an inactive AIS or smaller vessels under 300 gross tonnes that are not obliged to equip one [42].

In addition, current reactive collision avoidance approaches rely on ideal obstacle classification. Specifically, not only the obstacle's information but also its identity is fully known, for instance classified as a "vessel" or an "island", assuming an obstacle classification system. However, the accuracy of classification heavily relies on the quantity and quality of the trained data set and is vulnerable to producing false positives or false negatives when an unknown obstacle is detected [43]. Also, COLREGs-compliant evasive manoeuvres are only required when both vessels are underway [44], thus, rendering the reliance on obstacle classification for safe and efficient collision avoidance highly debatable.

For the reasons mentioned above, the proposed idea aims to develop a reactive collision avoidance system for MASS with robust decision-making and scenario-classification capabilities amidst limited sensory information and unclassified surface obstacles. The novel contribution is the critically limited the sensing area compared to the manoeuvrability of the vessel to enhance the reactiveness of the collision avoidance system even when the obstacle's information cannot be acquired a priori. Also, the system relies on scenario-classification to react accordingly rather than on obstacle-classification, in order to increase its survivability under unknown unknowns where only the least amount of information can be acquired.

4.2. METHODOLOGY

The proposed idea is formulated into a systematic methodology that is divided into 4 main phases, as shown in Figure 1. Particularly, Phase 1 considers the development of a high-fidelity digital twin environment suitable for virtual simulations. Main components entail the modelling of the digital map, such as the resolution and dimensions of the virtual obstacles, the ship dynamics that can simulate the manoeuvrability characteristics of the investigated vessel, and the onboard sensors, such as their field of view, resolution, and maximum detection range.

Phase 2 considers the development and training of an AI-based agent for collision avoidance decision-making. The appropriate decision-making objectives are defined, such as path following, collision avoidance, and COLREGs compliance. A DRL-based algorithm is employed to develop the agent and its hyperparameters are tuned to increase the quality of decision-making. The developed agent is trained where it interacts with the digital twin environment and learns how to make collision avoidance decisions in both static and dynamic scenarios. During the training, scenario-classification data are generated for the next phase.

Phase 3 entails the development and training of an AI-based agent for collision scenario-classification. A DL-based algorithm is employed to develop the agent and its hyperparameters are tuned to increase the accuracy of classification. The generated classification data are pre-processed to include only the most critical input data, whereas, the scenarios generated during the DRL agent's training are used to label the data. The developed agent uses the pre-processed data to learn to classify the scenario according to the labelled data.

Phase 4 considers the verification of the agents' robustness within and outside the training envelope. Specifically, various qualitative and quantitative robustness metrics for both agents are defined, such as collision avoidance efficiency and scenario-classification accuracy. A wide spectrum of simulations within the training envelope are generated to verify the robustness of the agents. Finally, a wide spectrum of simulations outside the training envelope are generated to stress-test the robustness of the agents, such as using different obstacle size, shape, and location.

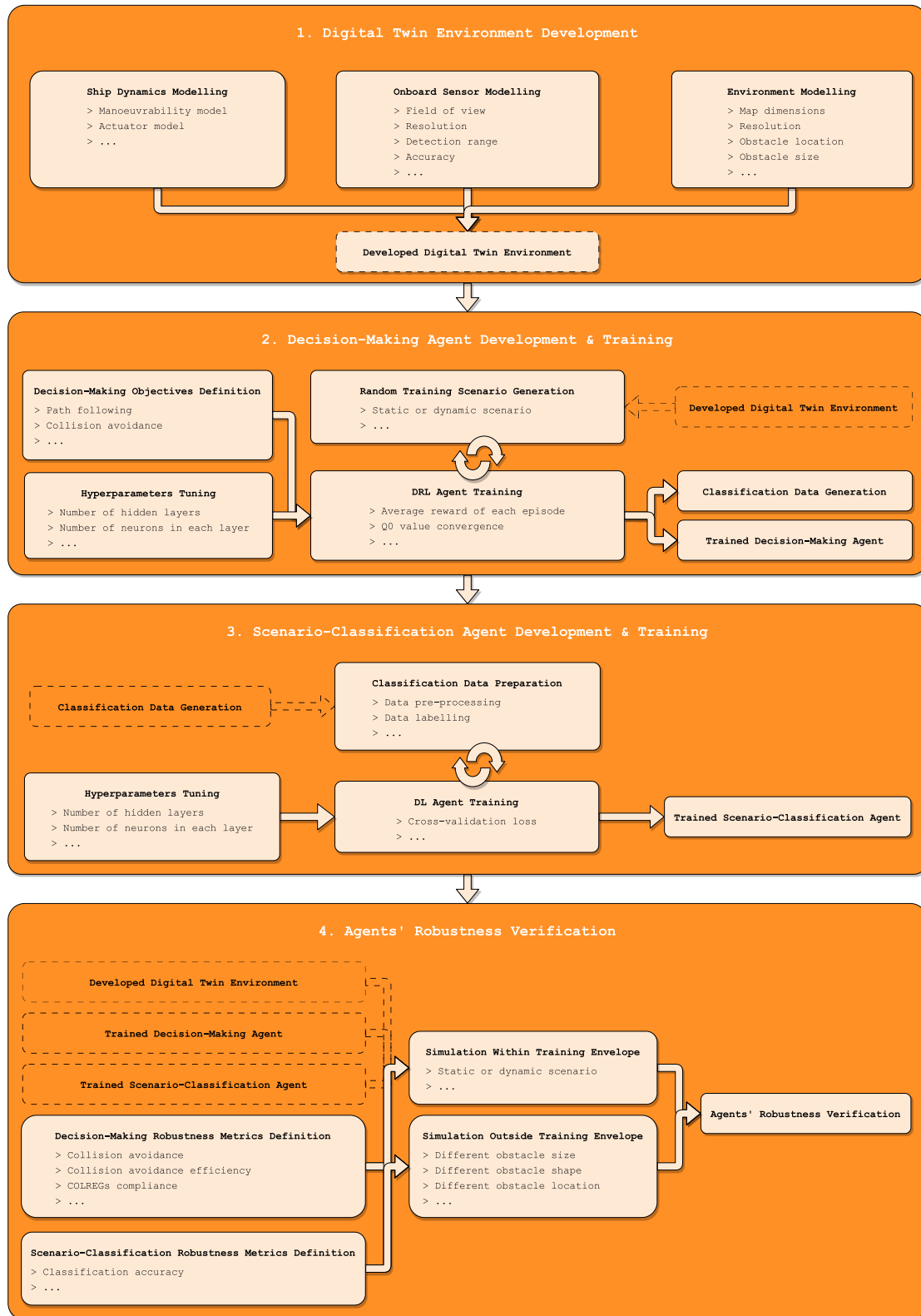


Figure 1 Methodology of the proposed idea presented as a block diagram.

5. DESIGN DESCRIPTION

5.1. DIGITAL TWIN ENVIRONMENT

The environment is designed as a 3x4 km² open sea area, where a predefined global path is provided as a straight-line for the MASS to follow. In every new training episode, the environment has a 50% chance of generating either a static or dynamic obstacle of radius (r_{obs}) 87.5 m, as shown in Figure 2. In the static scenario, the obstacle is randomly allocated to obstruct the global path. In the dynamic scenario, the obstacle is randomly allocated to lead into a port-side/starboard crossing or head-on encounter. Also, the dynamic obstacle maintains its speed and heading imposing risk of collision accident if no actions are taken from MASS. Both cases represent highly-collision inducing scenarios as collision with other ships that are not underway, contacts with floating objects, and violation of COLREGs rules constitute as much as 21% [18], 30% [45], and 56% [46] of the global maritime accidents, respectively.

The investigated vessel is a single-screw high-speed container ship, known as the S-175 [47]. A 4 Degrees Of Freedom (DOF) MMG model is employed for high-fidelity manoeuvring simulations [48], whose validity for calm and deep waters has been verified [49]. The investigated vessel is considered to maintain constant propeller revolution, whereas, a first order linear differential equation of its steering system is used to control the rudder angle [50]. For the onboard sensor, a 2D LiDAR is used due to its high frequency and precision of distance and angle measurements of surface obstacles, even for small ones [51]. Also, the maximum detection range is set to be equal to the maximum transfer distance of the vessel's turning circle manoeuvre in order to critically limit the sensing area compared its manoeuvrability, as shown in Figure 3. The main particulars of these models are presented in Table 3.

Table 3 Main particulars of the investigated vessel, steering system, and LiDAR sensor.

Digital Twin	Particular	Value
S-175 Container Vessel	Length between perpendiculars (L)	175 m
	Breadth (B)	25.4 m
	Displacement volume	21,200 m ³
	Nominal speed (U)	10.4 m/s
Steering System	Rudder area ratio	1/45.0
	Rudder aspect ratio	1.8219
	Maximum rudder angle	35 deg
	Maximum rudder deflection rate	5 deg/s
LiDAR Sensor	Field of view	225 deg
	Horizontal resolution	5.6 deg
	Number of LiDAR points	41
	Maximum detection range	1341 m

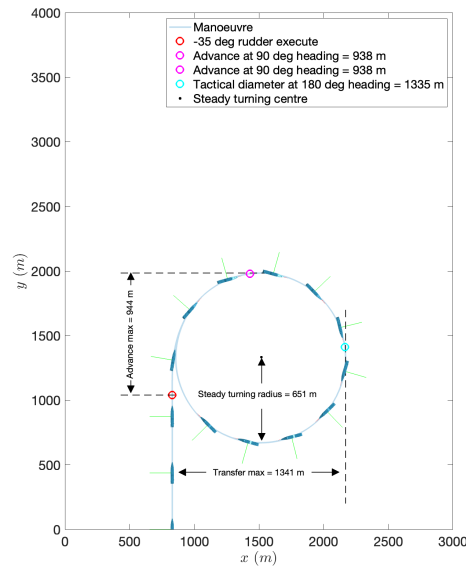


Figure 3 Turning circle manoeuvring characteristics of the investigated vessel.

For the development of the scenario-classifying agent, a DL-based fully connected feedforward ANN is employed due to its robust feature extraction capabilities [34]. The least amount of available information that consists of the vessel's states and the magnitude, velocity, and acceleration of the minimum LiDAR measurement generated during the decision-making agent's training is used as input data to the scenario-classification agent, whereas, the scenario of each training episode is used to label the data. The agent learns to output the correct scenario-classification with the main goal of minimising the classification error expressed as the cross-validation loss. The hyperparameters of both agents are presented in Table 4.

Table 4 Hyperparameters of the decision-making and scenario-classification agents.

Decision-Making Agent	Actor Network	Number of hidden layers	2
		Number of neurons in each hidden layer	500, 500
		Activation functions	ReLU, tanh
	Critic Network	Number of hidden layers	2
		Number of neurons in each hidden layer	400, 400
		Activation function	ReLU
Scenario-Classification Agent	Number of hidden layers		2
	Number of neurons in each hidden layer		86, 93
	Activation functions		tanh, softmax

5.3. ROBUSTNESS METRICS

Robustness stands for 'the degree to which a system can function correctly in the presence of invalid inputs or stressful environmental conditions' [54]. In this case, the degree to which the trained agents can make optimal decisions and accurate scenario classification in highly collision-inducing scenarios is investigated by defining various Robustness Metrics (RM). For the decision-making agent, a quantitative RM is defined to represent a successful collision avoidance as the minimum LiDAR measurement (RM_{CA}). In static scenario, a qualitative RM is defined to represent the collision avoidance efficiency as a port or a starboard side evasive manoeuvre that is closer to the path (RM_{CAE}). In dynamic scenario, a qualitative RM is defined as a COLREGs-compliant evasive manoeuvre (RM_{CC}). For the scenario-classifying agent, a quantitative RM is defined to represent the accuracy of classification as the fraction of the total number of correct classifications to the total number of classifications (RM_{SCA}).

6. RESULTS & DISCUSSION

The robustness of the decision-making and scenario-classification agents is verified in a wide spectrum of simulations within the training envelope, as shown in Figure 4 and Table 5. Particularly, various static obstacle allocations on the global path, 0° and 45° starboard crossing, 90° head-on, and 135° and 180° port-side crossing of a dynamic obstacle are simulated. The decision-making agent's robustness is verified with $RM_{CA} = [109.3 \text{ m}, 208.9 \text{ m}]$ and RM_{CAE} in the static scenario, and $RM_{CA} = [118.4 \text{ m}, 304.6 \text{ m}]$ and RM_{CC} in the dynamic scenario, even when the dynamic obstacle does not comply to the COLREGs rules. The scenario-classifying agent's robustness is verified with $RM_{SCA} = [96.8\%, 99.7\%]$ and $[97.9\%, 100\%]$ in the static and dynamic scenario, respectively. In all simulations, both agents run faster than real-time.

To further stress-test the agents' robustness, a wide spectrum of simulations outside of the training envelope are conducted, as shown in Figure 5 and Table 5. Specifically, various obstacles of different sizes and shapes are generated. Also, the number of LiDAR points are increased from 41 to 401 to resemble a more realistic configuration for real-world applications and the minimum of every 10^{th} LiDAR measurement is used instead to comply to the initial hyperparameter setting. The derived simulation results verify the decision-making agent's robustness with $RM_{CA} = [87.6 \text{ m}, 213.2 \text{ m}]$ and RM_{CAE} in the static scenario, and $RM_{CA} = [121.7 \text{ m}, 265.1 \text{ m}]$ and RM_{CC} in the dynamic scenario, even when the dynamic obstacle does not comply to the COLREGs rules. The scenario-classifying agent's robustness is verified with $RM_{SCA} = [82.8\%, 99.7\%]$ and $[91.2\%, 100\%]$ in the static and dynamic scenario, respectively.

It is worth noting that the developed system can handle a wide range of static and dynamic obstacles, $r_{\text{obs}} = 4\text{-}470 \text{ m}$ and $L_{\text{obs}} = 12\text{-}104 \text{ m}$. This range of sizes and shapes resemble various surface obstacles, such as from a floating container box to a large iceberg and from a small boat to a mid-sized yacht that are most likely not to be equipped with an AIS. Finally, the derived results verify the robustness of the system to conduct efficient collision avoidance by generating a COLREGs-compliant evasive manoeuvre only when an unclassified surface obstacle is underway, as shown in the g) and h) subplots of Figure 5, thus, saving total travelled distance and energy consumption.

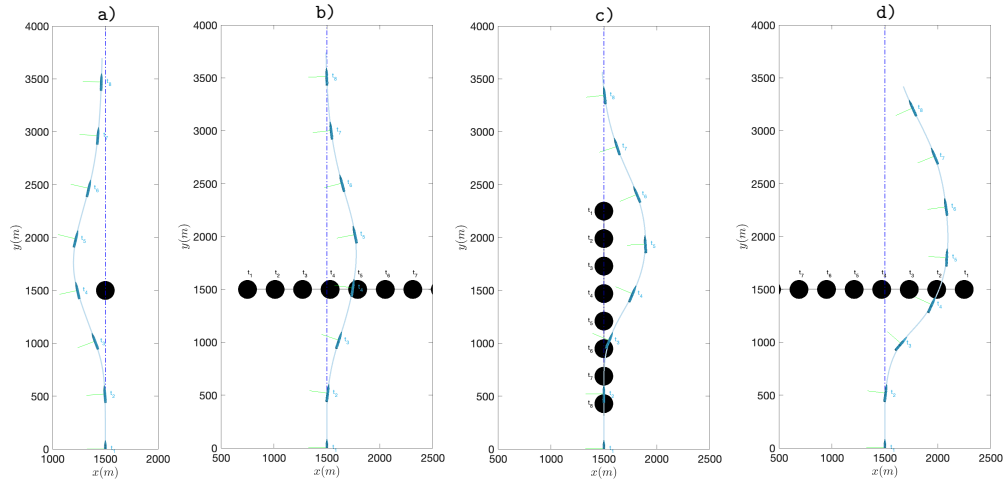


Figure 4 Simulations within the training envelope: a) $r_{obs} = 87.5$ m static, b) $r_{obs} = 87.5$ m 0° starboard crossing, c) $r_{obs} = 87.5$ m 90° head-on, d) $r_{obs} = 87.5$ m 180° port-side crossing.

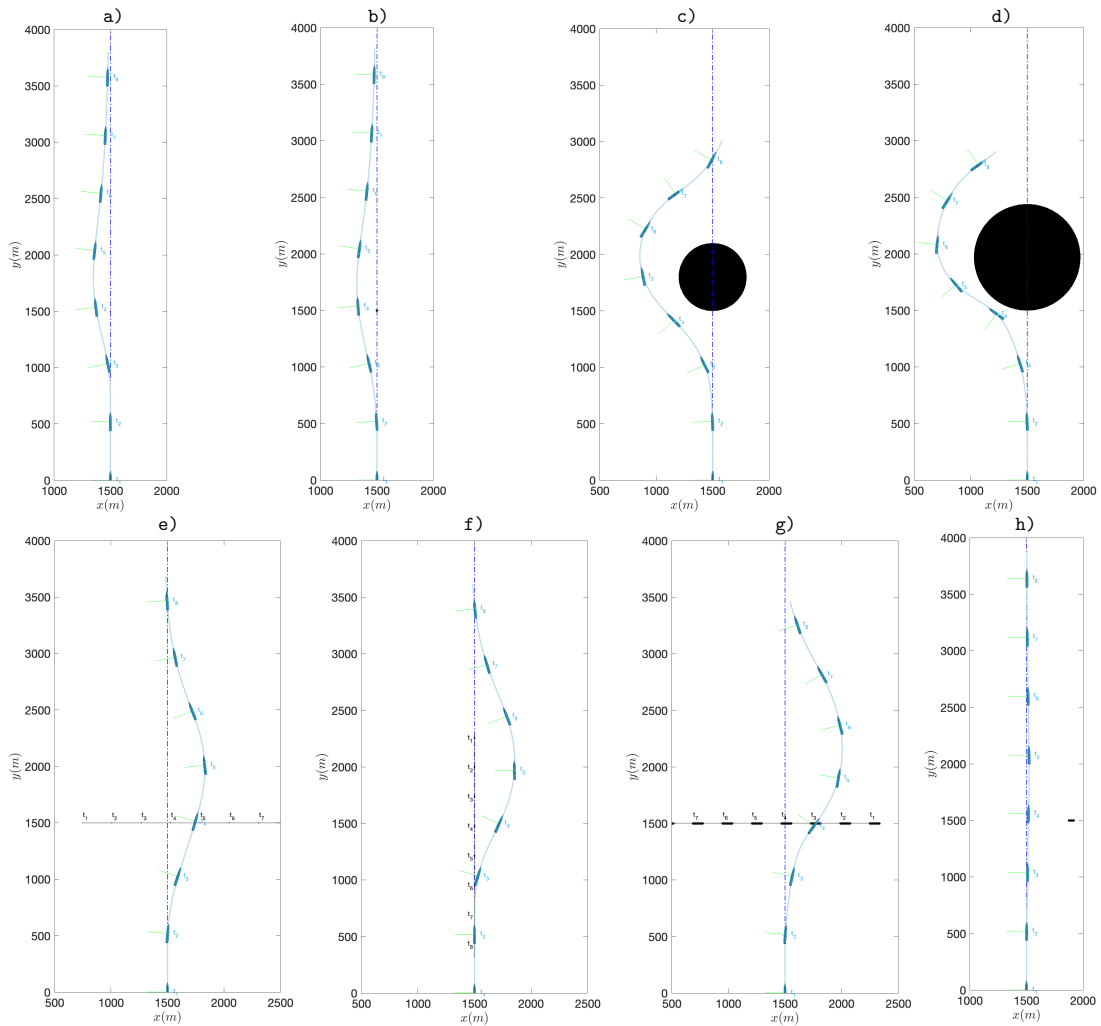


Figure 5 Simulations outside the training envelope: a) $r_{obs} = 4$ m static, b) $r_{obs} = 10$ m static, c) $r_{obs} = 300$ m static, d) $r_{obs} = 470$ m static, e) $L_{obs} = 12$ m 180° port-side crossing, f) $L_{obs} = 23$ m 90° head-on, g) $L_{obs} = 104$ m 0° starboard crossing, h) $L_{obs} = 104$ m static.

Table 5 Robustness verification of the decision-making and scenario-classification agents. The heatmap represents the following: ‘●’ for ‘satisfied’ and ‘●’ for ‘not satisfied’.

Robustness Verification Within Training Envelope					
Static Scenario (1/1)	● $r_{obs} = 87.5$ m $CTE_{obs} = -175.0$ m	● $r_{obs} = 87.5$ m $CTE_{obs} = -87.5$ m	● $r_{obs} = 87.5$ m $CTE_{obs} = 0$ m	● $r_{obs} = 87.5$ m $CTE_{obs} = 87.5$ m	● $r_{obs} = 87.5$ m $CTE_{obs} = 175.0$ m
RM _{CA}	146.3 m	109.3 m	164.6 m	190.7 m	208.9 m
RM _{CAE}	●	●	●	●	●
RM _{SCA}	96.8%	99.7%	98.9%	98.9%	98.4%
Dynamic Scenario (1/1)	● $r_{obs} = 87.5$ m $U_{obs} = 5.2$ m/s 180° crossing _{overtake}	● $r_{obs} = 87.5$ m $U_{obs} = 5.2$ m/s 135° crossing _{overtake}	● $r_{obs} = 87.5$ m $U_{obs} = 5.2$ m/s 90° head-on	● $r_{obs} = 87.5$ m $U_{obs} = 5.2$ m/s 45° crossing _{overtake}	● $r_{obs} = 87.5$ m $U_{obs} = 5.2$ m/s 0° crossing _{overtake}
RM _{CA}	118.4 m	123.1 m	171.4 m	231.2 m	304.6 m
RM _{CC}	●	●	●	●	●
RM _{SCA}	97.9%	98.7%	99.7%	100%	100%
Robustness Verification Outside Training Envelope					
Static Scenario (1/1)	● $r_{obs} = 4$ m $CTE_{obs} = 0$ m	● $r_{obs} = 10$ m $CTE_{obs} = 0$ m	● $r_{obs} = 30$ m $CTE_{obs} = 0$ m	● $r_{obs} = 300$ m $CTE_{obs} = 0$ m	● $r_{obs} = 470$ m $CTE_{obs} = 0$ m
RM _{CA}	116.2 m	150.5 m	162.6 m	213.2 m	87.6 m
RM _{CAE}	●	●	●	●	●
RM _{SCA}	98.4%	99.7%	99.7%	92.0%	82.8%
Dynamic Scenario (1/3)	● $L_{obs} = 12$ m $B_{obs} = 5$ m 180° crossing _{overtake}	● $L_{obs} = 12$ m $B_{obs} = 5$ m 135° crossing _{overtake}	● $L_{obs} = 12$ m $B_{obs} = 5$ m 90° head-on	● $L_{obs} = 12$ m $B_{obs} = 5$ m 45° crossing _{overtake}	● $L_{obs} = 12$ m $B_{obs} = 5$ m 0° crossing _{overtake}
RM _{CA}	213.6 m	171.1 m	121.7 m	235.8 m	223.8 m
RM _{CC}	●	●	●	●	●
RM _{SCA}	100%	99.5%	99.5%	97.9%	94.1%
Dynamic Scenario (2/3)	● $L_{obs} = 23$ m $B_{obs} = 9$ m 180° crossing _{overtake}	● $L_{obs} = 23$ m $B_{obs} = 9$ m 135° crossing _{overtake}	● $L_{obs} = 23$ m $B_{obs} = 9$ m 90° head-on	● $L_{obs} = 23$ m $B_{obs} = 9$ m 45° crossing _{overtake}	● $L_{obs} = 23$ m $B_{obs} = 9$ m 0° crossing _{overtake}
RM _{CA}	212.1 m	179.9 m	196.6 m	242.7 m	265.1 m
RM _{CC}	●	●	●	●	●
RM _{SCA}	100%	100%	99.2%	98.1%	91.2%
Dynamic Scenario (3/3)	● $L_{obs} = 104$ m $B_{obs} = 19$ m $U_{obs} = 5.2$ m/s 180° crossing _{overtake}	● $L_{obs} = 104$ m $B_{obs} = 19$ m $U_{obs} = 5.2$ m/s 135° crossing _{overtake}	● $L_{obs} = 104$ m $B_{obs} = 19$ m $U_{obs} = 5.2$ m/s 90° head-on	● $L_{obs} = 104$ m $B_{obs} = 19$ m $U_{obs} = 5.2$ m/s 45° crossing _{overtake}	● $L_{obs} = 104$ m $B_{obs} = 19$ m $U_{obs} = 5.2$ m/s 0° crossing _{overtake}
RM _{CA}	193.8 m	180.3 m	207.2 m	262.0 m	126.2 m
RM _{CC}	●	●	●	●	●
RM _{SCA}	99.7%	98.9%	98.1%	100%	93.8%

7. CONCLUSIONS & FUTURE WORK

The proposed idea aimed at developing a reactive collision avoidance system for MASS with robust decision-making and scenario-classification capabilities amidst limited sensory information and unclassified surface obstacles. A high-fidelity digital twin environment was developed, and 2 AI-based agents were developed and trained for decision-making and scenario-classification. Various robustness metrics were identified to evaluate the agent's robustness. The proposed idea contributes towards a more

sustainable maritime industry with higher levels of safety and efficiency through the development of robust AI systems in safety-critical applications considering the following main findings:

- The developed system can conduct safe and efficient reactive collision avoidance in real-time even when the sensing area is critically limited and amidst unclassified surface obstacles.
- The scenario-classification agent can identify a static or dynamic scenario based on the least amount of information available with an accuracy above 82.8%.
- The decision-making agent can generate collision avoidance manoeuvres even when the scenario-classification is not 100% accurate and amidst a wide range of obstacle shapes and sizes resembling surface obstacles with radii of 4-470 m and target vessels ranging from 12-104 m in length that are more likely not to be equipped with an AIS, while complying to the COLREGs rules, even when the dynamic obstacle does not comply to the rules.
- The strength of trained AI-based agents to generalise their knowledge even in different system configurations and unseen scenarios has been noted.
- The advantage of scenario-classification based collision avoidance rather than based on obstacle-classification to save energy consumption via minimising travelling distance is discussed due to its ability to avoid unnecessary COLREGs-compliant evasive manoeuvres when not needed.

The main identified technology gaps are the limited detection range of the current LiDARs, their high cost, and the lack of experiments to validate the technical feasibility and safety of the proposed idea. Future work includes the consideration of environmental disturbances, dynamic propeller revolution, and at investigation of a wider spectrum of simulations for the robustness verification.

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