Cooperative AI Techniques for Ocean Path Planning of Maritime Autonomous Surface Ships

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***Abstract*—This paper explores the use of Artificial Intelligence (AI) techniques for collaborative path planning in Maritime Autonomous Surface Ships (MASS). To improve both safety and efficiency in navigation, path planning is enhanced with AI-driven approaches that align with International Regulations for Preventing Collisions at Sea (COLREGs) set forth by the International Maritime Organization (IMO). The challenges of path planning, both at global and local levels, are addressed to emphasize the role of the cooperation among vessels in optimizing the AI performance. Furthermore, various cooperative frameworks are discussed by focusing on technical aspects, such as sharing positional and control data between vessels, and by developing advanced message-passing methods to enhance real-time navigation accuracy. Finally, a feasibility study is investigated presented, showing the potential of AI-based cooperative strategies to lower collision risks and boost the maritime navigation effectiveness.**

I. Introduction

The growth of global economy continues to lead a rapid increase in the scale of the international trade [1]. This expansion has driven the demand for maritime transport services [2]. A large number of vessels have their own various paths over coastal areas, potentially resulting in bottlenecks in waterways [3]. Furthermore, the congestion caused by route overlaps increases the risk of collisions, thus slowing down the global ocean traffic. The international maritime organization (IMO) has established a set of safety rules for collision avoidance, known as convention on the international regulations for preventing collisions at sea (COLREGs) [4] [5]. These rules serve as guidelines for navigation, ensuring that, when two vessels encounter each other, they take appropriate collision avoidance actions by recognizing their positions and paths.

A vessel navigates according to a route schedule obtained through path planning. Path planning finds a feasible course from origin to destination with the consideration of maritime obstacles and legal requirements [7]. As a result, a large number of vessels navigate along various paths in coastal areas, which can incur bottlenecks in waterways [6]. MASS relies on situational awareness (SA) to support path planning [7]. SA involves gathering accurate information about the surrounding terrain and the movements of nearby vessels, along with control details like thrust and rudder angle. MASS uses a data-driven approach, supported by artificial intelligence (AI), to obtain control information for path planning [2], [8], [9]. AI analyzes real-time SA data to find paths that help the vessel avoid collisions with other vessels [10].

Multiple MASS via the cooperation through the exchange of SA lead to the enhancement of path planning among individual MASS [11]. MASS can obtain location and control information from other vessels by sharing SA in real-time to update the SA information with details about nearby obstacles and vessel positions. The cooperative path planning strategies have investigated the collaborative maritime operations to enhance SA [2], [11], [12]. The exchange of the location data enhances the vessel coordination [13]. Furthermore, the sharing of control information develops additionally detailed understanding of the operational environment [14]. The exchange of messages that incorporate both location and control information offers a balanced approach to cooperative maritime operations.

This paper presents AI-based cooperation policies that enable the MASS navigation to comply with COLREGs. The paper consists of the following content. It investigates vessel dynamics, explaining the principles of collision avoidance and providing a detailed analysis about COLREGs. It then conducts a comprehensive review of AI techniques pertinent to the conceptualization of local and global path planning. The study further delves into various cooperative frameworks designed to enhance SA, offering a evaluation of these systems. Finally, the paper presents a case study about the implementation of cooperative frameworks followed by concluding remarks about the realistic deployment.

II. Autonomous Navigation

Understanding vessel dynamics is necessary for path planning and cooperation among vessels. This section introduces the fundamental theory of vessel dynamics. In addition, the international regulations for ocean traffic of vessels are presented, which are key components for developing AI-assisted MASS navigation techniques.

A. Vessel dynamics

The dynamics of the vessel is determined by several physical features, such as locations, controls, and geographical configurations [15]. A vessel moves through a control input of the thrust and the rudder angle, represented by a vector $\boldsymbol{\tau}$. The location of a vessel is updated according to the control input.

The location vector $\boldsymbol{\eta}$ consists of two-dimensional coordinates x, y and heading angle ψ as $\boldsymbol{\eta} = [x, y, \psi]^T$. This vector $\boldsymbol{\eta}$ is referred to as the location information of SA and is obtained with respect to earth-fixed reference frame defined by latitude and longitude coordinates. Furthermore, the velocity vector $\boldsymbol{v}$ is characterized by surge velocity u, sway velocity, v, and yaw rate r as $\boldsymbol{v} = [u, v, r]^T$, which is evaluated with respect to the body-fixed frame, a coordinate system attached to itself. Since $\boldsymbol{\eta}$ and $\mathbf{v}$ are defined with respect to different coordinates, a transformation is necessary to align them in the same reference frame. This can be achieved by using a rotation matrix $\mathbf{T}(\psi)$ for a given vessel heading angle ψ, which is defined as

$$\mathbf{T}(\psi) = \begin{bmatrix} \cos\psi & -\sin\psi & 0 \\ \sin\psi & \cos\psi & 0 \\ 0 & 0 & 1 \end{bmatrix}. \tag{1}$$

The time derivative of the location obtains the velocity as

$$\dot{\boldsymbol{\eta}} = \mathbf{T}(\psi)\mathbf{v}. \tag{2}$$

Therefore, the temporal change of $\boldsymbol{\eta}$ can be accurately estimated from the transformed velocity vector, and the resulting displacement and the position of the vessel are predicted.

Furthermore, several forces including Coriolis force, centripetal forces, drag, friction, buoyancy, and gravity are exerted together to the vessel when control input $\boldsymbol{\tau}$ is applied. The resulting dynamics is described as [15]

$$\mathbf{M}\dot{\mathbf{v}} + \mathbf{C}(\mathbf{v})\mathbf{v} + \mathbf{D}(\mathbf{v})\mathbf{v} + \mathbf{g}(\boldsymbol{\eta}) = \mathbf{B}\boldsymbol{\tau}, \tag{3}$$

where $\mathbf{M}$ is the mass and inertia matrix of the vessel that represents the resistance to changes in motion, $\mathbf{C}(\mathbf{v})$ stands for the Coriolis and centripetal forces for a given velocity vector $\mathbf{v}$, $\mathbf{D}(\mathbf{v})$ indicates the resistive force that includes drag and friction, $\mathbf{g}(\boldsymbol{\eta})$ denotes the restoring forces originating from gravity and buoyancy helping maintain the stability, and the control allocation matrix $\mathbf{B}$ converts the control input $\boldsymbol{\tau}$ into forces and moments that act on the vessel. As a result, the acceleration of the vessel $\dot{\mathbf{v}}$ can be computed based on the current location information vectors together with control input $\boldsymbol{\tau}$. Once the acceleration is calculated, the change in velocity can be obtained and the velocity updates are available. Plugging this updated velocity into (2), the vessel position updates made during the unit time step are calculated. By repeating this calculation, the overall motion of the vessel can be accurately described and controlled in response to the input and the current location.

B. Collision avoidance

For the purpose of navigation safety, collision avoidance techniques are essentially required for the design of the MASS path planning algorithm. Maritime navigation plans normally comply with COLREGs established by IMO [4], [5]. COLREGs include 41 fundamental collision avoidance rules divided into six different categories, such as steering, sailing, sound, and light signals [9]. Fig. 2 illustrates several important rules relevant to collision avoidance, which are summarized as in the following.

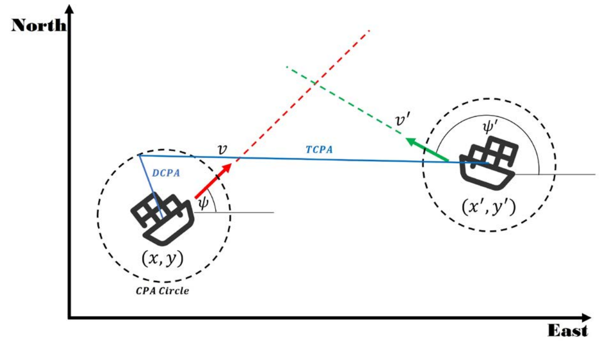

Fig. 1: Vessel control model for collision avoidance event.

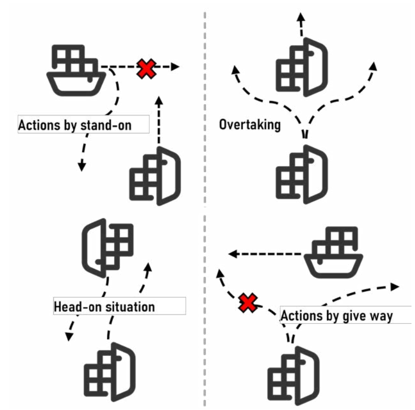

Fig. 2: Encounter situations described by COLREGs.

- **Overtaking (Rule 13):** Any vessel overtaking another must keep out of the way of the vessel being overtaken.
- **Head-on situation (Rule 14):** Each vessel must alter its course to starboard to pass on the port side of the other.
- **Crossing situation (Rule 15):** The vessel with the other on its own starboard side must keep out of the way.
- **Actions by give-way vessel (Rule 16):** Early and substantial action is required to ensure a safe distance is maintained.
- **Actions by stand-on vessel (Rule 17):** The stand-on vessel should maintain its course and speed, but can take evasive action if the other vessel does not comply with COLREGs.

These rules provide the foundation of safe and compliant vessel controls for autonomous navigation systems. Adhering to these guidelines, autonomous vessels can navigate complex maritime environments while minimizing the risk of collisions.

The compliance of COLREGs is normally assessed in terms of two risk indicators about the occurrence of collision events: closest point of approach (CPA) and collision risk index (CRI) [10]. CPA measures the distance between the closest points that two vessels approach when they stick to their current paths. Also, CRI offers comprehensive assessment by incorporating distance and time information. For the evaluation, it is necessary to leverage additional parameters such as time closest point of approach (TCPA) and distance closest point of approach (DCPA). TCPA is the time until one vessel maintaining the current path reaches the closest point to the other vessel, while DCPA is the corresponding distance between two vessels on the closest points. Most collision avoidance techniques determine control output $\boldsymbol{\tau}$ by minimizing some aggregated functions of these two risk indices.

III. Path planning of MASS

The MASS path planning task targets to obtain a series of location and control vectors that the vessel should process at individual time instants. According to the time scale and the navigation range, the MASS path planning is classified into global path planning and local path planning [16]. Global path planning determines a long-term navigation path by identifying waypoints that interconnect origin and destination positions. By contrast, in the local path planning, detailed trajectories between two waypoints are found by optimizing short-term MASS movement features, e.g., speeds and heading angles. This section reviews several path planing approaches based on global and local path planning techniques.

A. Global path planning

Efficient global path planning relies on carefully designed waypoints that satisfy diverse navigation goals, including travel time/distance minimization, energy consumption, and safety indicators. Such nested path planning tasks cannot be addressed directly via existing shortest-path algorithms. To handle this, automatic identification system (AIS) [17] collects real-time navigation trajectories, including positions, speeds, and courses. AI techniques can utilize historical features of these datasets to enhance the global path planning performance [18], [19], [20].

Data-driven approaches are useful, in particular, for saving the energy consumption in global path planning. A number of difficult-to-measure parameters in marine environments affect energy usage of vessel. This makes building mathematical models for prediction challenging. AI techniques can infer current ocean conditions from historical navigation data in AIS by using data-driven methods. In [21], the vessel navigation in the arctic region is focused by developing a neural network based model. Thick ice in arctic regions renders selecting waypoints critical and challenging, since vessels cannot pass over it and fail to navigate the region. This approach analyzes past data to detect patterns among the ice concentration, vessel speed, and energy efficiency, finding fuel-efficient and feasible routes.

Global path planning in regions with significant environmental changes between waypoints demands not only evaluating waypoints but also predicting intermediate waypoints. This dense waypoint setup relies on predicting future positions of the vessel. A deep neural network (DNN), trained with turning point data from AIS, predicts these future positions. A iterative update approach using recurrent neural network (RNN) [22] is employed to predict the intermediate waypoint. The fixed waypoint, the expected location the vessel will reach, is generated using historical data, while a trained long short-term memory (LSTM) model produces the intermediate waypoint.

Another factor in the waypoint selection for global path planning is planned mission of the vessel. The sequence of waypoints changes depending on the mission, and optimizing these routes is known as multi-task path optimization. This problem is approached as a traveling salesman problem, where the objective is to visit multiple locations efficiently. A self-organizing map-based DNN [23] is applied to determine the optimal sequence for visiting water monitoring stations, minimizing travel time and distance by learning the best order to visit these stations based on their spatial distribution.

B. Local path planning

Small-scale navigation strategies between waypoints are designed by the local path planning. Unlike global path planning that operates with long-term movement features, finding the local paths heavily relies on real-time dynamics and surrounding environments. It also needs to capture the short-term changes incurred by nearby vessels, in particular, over congested areas, e.g., ports and waterways [24].

Traditional algorithms have mainly focused on sea and weather conditions and nonlinear vessel dynamics for several key limitations [25]. High computational complexity arises when mathematical models for collision avoidance try to account for numerous variables in real-time, which is challenging in dynamic environments with multiple vessels. Another major problem is that many of these traditional algorithms are built on predefined frameworks that use fixed rules to handle specific scenarios. These frameworks often rely on oversimplified assumptions, such as ignoring the variability in vessel behavior or environmental factors, leading to inaccurate risk assessments. Most traditional studies address only single obstacles at a time, and their strategies readily become impractical in crowded maritime environments.

To address these challenges, the deep reinforcement learning (DRL) framework can be adopted which employs AI-enabled agents to determine MASS navigation policies in real time [26]. Local path planning tasks are formalized as Markov decision processes. DRL agents are trained to take successful navigation actions of MASS to maximize rewards regarding navigation efficiency and safety. Inputs for DRL-based solutions can include any states of overall systems, such as MASS dynamics and surrounding environments.

A DRL model navigates the vessel by interacting with its environment in real time, guided by a reward function [27]. The vessel earns a cumulative reward of reaching its destination, avoiding collisions, and maintaining a proper distance from other vessels according to COLREGs [28]. Another approach mainly focuses on assigning different rewards according to specific situations of COLREGs [29]. This approach first identifies a situation of COLREGs to identify the corresponding valid reward function and, subsequently, the OS takes an action according to the resulting reward until the collision alert is resolved. This approach uses a dedicated DNN that predict a valid situation out of the cases described by determine COLREGs from the position information among the OS and surrounding TSs. The DRL model then learns to control the vessel according to the situation-specific rewards. This reward change ensures that the vessel can balance path planning for dynamic responses to potential collision risks.

When processing the surrounding information, a vessel encounters many TSs, causing constant fluctuations in the number of relevant states the AI must handle. Neural networks, however, demand a fixed input size, which complicates the solution for multi-vessel encounters. One technique addresses this challenge by using the last five records of detected distances to obstacles as input for the DNN [28]. Another technique categorizes TSs into four regions based on COLREGs, reducing the input dimensions to four [27]. Furthermore, some technique combine long short-term memory (LSTM) with sequence conditional generative adversarial networks (GANs) [30]. This approach learns 12 different vessel encounter patterns from AIS data, which allows to process surrounding information and make human-like the navigation for the collision avoidance.

IV. Cooperative MASS Navigation

Vessels require accurate measurement of the information about nearby TSs to avoid the collision. In case of independent operation without direct communication among vessels, however, individual vessels only have the access to basic summaries like speed and direction through radar and AIS. Such incomplete records force the navigation schedule to assume constant movement of neighboring vessels, thereby resulting in degraded predictions of TS positions. An advanced method is the cooperation among vessels through inter-vessel communication network, so that the information, such as real-time positions, intended courses, and any modifications to environmental changes, is shared. This data exchange enhances SA, maintaining accurate information of the surrounding terrain and the movements of nearby vessels [7]. Enhanced SA achieves the improvement of vessel coordination.

A simple way to implement cooperation in the collision avoidance exchanges the position information about real-time positions, speeds, and courses [13]. This information helps vessels develop shared understanding of the movements of other vessels and includes critical risk metrics like the CPA. Vessels share this data to assess potential collision risks accurately and make others informed adjustments to their courses. Another cooperation strategy consists in communicating the control information, including steering intentions, rudder commands, and speed changes, along with the location information. Upon sharing these details, vessels understand planned maneuvers of others to make the informed modification to their own courses and speeds to secure safe distances [14]. Furthermore, vessels can exchange previous trajectories so that other vessels can predict future movements [12]. Thus, vessels anticipate and respond to potential collision risks by altering paths and speeds in a timely manner.

A further enhanced cooperation among vessels involves the exchange of messages about the latent information that is learned from data point space constructed jointly by location and control information. Thus, vessels can exchange implicitly encoded information in terms of messages so that their real-time position, speed, course, and intended maneuvers are shared with neighboring vessels. Once messages are exchanged, a vessel combines the received data with its own observations, using comprehensive inputs to determine next actions.The integration of the information from nearby vessels resolves multiple encounters among vessels.

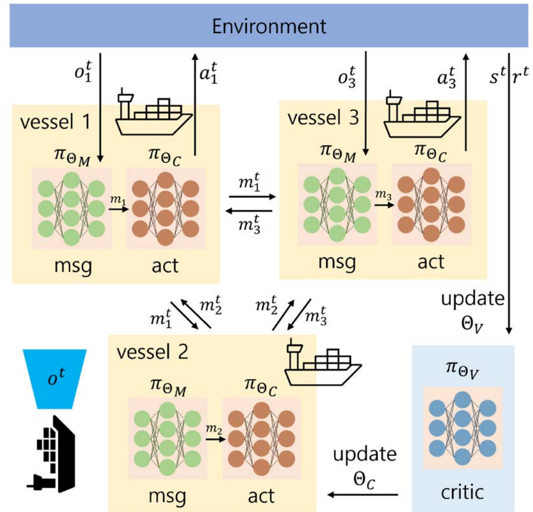

Fig. 3: Training structure of message-passing path planning cooperation.

To assure the feasibility of the aforementioned cooperation principles, an implementation example of realizing the cooperation that exchanges a latent-space encoded message about the combined location and control information. Fig. 3 illustrates the structure of the latent-message neural network. At time slot t, individual vessels make their navigation actions a^t based on observations o^t that are measured from surrounding environments. For the cooperation with neighbors, each vessel generates a message m^t with a message-generating network, denoted by π_{Θ_M} with a parameter set Θ_M, that takes the observation o^t as the input, and subsequently, this message which implicitly contains both location and control information in the latent space is shared with other vessels. The action a^t is generated by an action-generating network, denoted by π_{Θ_C} with parameter Θ_C, that uses both the observation o^t and the received message m^t at the input.

To train neural networks of the proposed framework, i.e., π_{Θ_M} and π_{Θ_C}, the proximal policy optimization (PPO) algorithm [31] is utilized. A critic network π_{Θ_V} with parameter Θ_V, which estimates the value function of motivation actions a^t, is introduced to train the actor networks. This training technique improves the policy of the vessel to obtain an improved navigating solution from local observations and exchanged messages.

Fig. 4. shows the performance comparison between the training computations with and without the message exchange

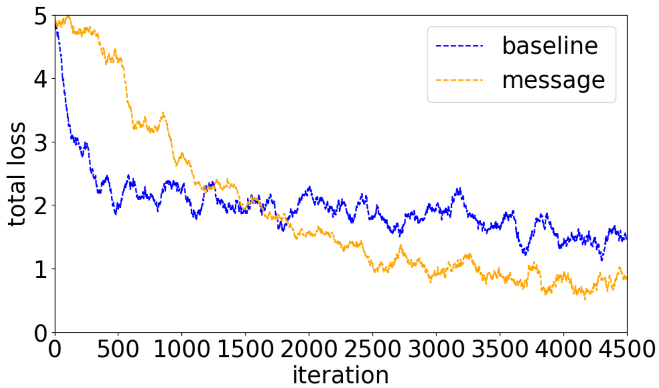

Fig. 4: Performance evaluation between path planning techniques.

in the MASS framework. Vessels move with random headings and speeds within a 20 km $\times$20 km region that is enclosed by a large circular terrain, within which the vessels must navigate. Each vessel follows a predefined dynamics equation, as previously described, with specific physical characteristics such as a length of 200 m, a maximum speed of 17 knots, and a DCPA of 1 km. The vessels start from random initial positions within the region, with the goal of reaching designated waypoints while avoiding collisions and minimizing travel time. The vertical axis represents the total loss function, while the horizontal axis shows the number of training iterations. Note that the message exchange slows down initial learning speed since the corresponding the network has more parameters to learn. However, as the computation goes on, the message exchange secures high and stable rewards. This indicates that incorporating the message exchange in AI path planning techniques improves the learning performance, since the exchanged message contribute to obtain better positions and higher rewards over times.

V. Conclusion

This paper has reviewed AI-driven approaches that support MASS for the path planning and the collision avoidance in accordance with COLREGs. The path planning techniques are normally pursued in two different approaches of global path planning, which sets a long-distance route across ocean areas, and local path planning, which focuses on navigating over coastal areas. To reinforce the path planning strategy with respect to time-varying and dynamic maritime environment, cooperative principles can be introduced among vessels. Such frameworks emphasize sharing location information about directions, positions, and speeds of vessels, as well as control information about thrust and rudder angle. To examine the feasibility of cooperative methods, an AI-based technique that implicitly encodes both location and control information from SA results of individual vessels into messages to share over neighboring vessels is proposed. The simulation results show that the exchange of compact messages that can provide latent information enhances the overall performance of training and inference computations, which sheds a light on potentials for the reliable MASS navigation.

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