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A collision avoidance algorithm with intention prediction for inland waterways ships

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Abstract: Collision avoidance is one of the most challenging problems in developing a Maritime Autonomous Surface Ship. This paper proposes a pro-active collision avoidance algorithm for inland waterway ships. The algorithm addresses the problem of avoiding collisions with dynamic obstacles by applying a situation-based intention prediction for neighboring ships. This prediction algorithm allows own ship to be aware of future collision threats caused by the course changes of nearby ships. The prediction scheme is integrated into a scenario-based model predictive control scheme that has been modified for application in inland waterway traffic. The proposed algorithm can deal with complex traffic situations that a ship can encounter, and the performance of the proposed algorithm is evaluated in several experiment simulations.

Keywords: Autonomous surface vehicles; Decision support systems; Optimal marine system control; Marine system navigation, guidance and control; Model predictive control.

1. INTRODUCTION

The recent decade has witnessed increased research towards Maritime Autonomous Surface Ship (MASS). One of the most crucial challenges is to guarantee the safe navigation of ships. Therefore, collision avoidance (COLAV) control is a core component of the control system of a MASS. The main task of collision avoidance is to safely navigate a ship from a start point to an end point while avoiding all obstacles. To achieve this task, many approaches have been proposed including: rule-based methods Tam and Bucknall (2013); Fang et al. (2018); virtual vector method Mahini et al. (2013); model predictive control (MPC) Zheng et al. (2016), or scenarios-based MPC Johansen et al. (2016); Tengesdal et al. (2020). A comprehensive review of the state-of-art COLAV algorithms can be found in Huang et al. (2020).

While most COLAV algorithms succeed in dealing with static obstacles, dealing with dynamic obstacles, on the other hand, is the most challenging problem. This problem is even more crucial in inland waterway traffic (IWT) because of the congested traffic and confined space available for maneuvering. Since the future position of dynamic obstacles is unknown, evaluating the collision risk for this type of obstacle is more complicated than for static obstacles.

The constant velocity model Shah et al. (2016) is a common solution for predicting the future position of dynamic obstacles. This model predicts the future position of neighboring ships based on a kinematic model with the assumption that the velocity vector of a neighboring ship (NS) is unchanged. However, this assumption can be impractical since a NS can change its course, especially in congested traffic. A learning-based prediction model could improve this limitation by utilizing historical traffic data, e.g., AIS data, to predict the behavior of a NS in traffic scenarios Scheepens et al. (2014); Hexeberg et al. (2017); Rong et al. (2019). That being said, a learning-based method depends on the training database and becomes less accurate when encountering a new type of behavior. A method widely used for land-based vehicles to improve the prediction model is implementing a rule-based prediction, Song and Li (2021). Accordingly, long-term prediction considers the traffic situation and rules to predict future positions regarding dynamic obstacles. This method cannot be applied directly to the maritime domain since ships have a wider range of available control actions than land vehicles due to the open environment, which also decreases the precision of long-term predictions. Another approach is the interaction-aware method, where the ships can exchange or negotiate their intentions through communication Akdağ et al. (2022); Zheng et al. (2017). The interaction-aware method can overcome most of the

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limitations of prediction methods. However, not all ships are willing or able to share or negotiate their intentions, especially human-crewed ships.

In recent decades, the inland waterway ship collision avoidance has received increasing attention from the research society, Zhang et al. (2022); Chen et al. (2020); Du et al. (2022). Differing from the open sea environment, the ship's operation in an inland waterway setting is limited by the bank and the water depth. The limited water depth causes a change in the hydrodynamics of ships, He et al. (2021), while the narrow water channel limits the ship's working space. Several types of control algorithm have been proposed to deal with these challenges, including: model predictive control, Helling et al. (2020), fuzzy control, Chen et al. (2021b), model-based tracking control, Vantorre, Marc and Laforce, E and Clayeyssens, P (1997), adaptive PID, Chen et al. (2021a). On the one hand, the narrow water channel restricts the sailing space of the ship, but on the other hand, it makes the intention of the NSs more predictable.

In view of the analysis above, we propose a collision avoidance (COLAV) algorithm for ships in inland waterways. This algorithm improves the safety navigation of a ship in complex traffic scenarios of IWT by using a situation-based prediction algorithm to forecast the potential collision probabilities. A similar approach, the probabilistic scenario-based MPC (PSB-MPC), can be found in Tengesdal et al. (2022), where the collision avoidance algorithm considers the intentions of NSs. The PSB-MPC primarily focuses on the intention of ships involved in the traffic scenario, e.g., head-on, crossing, or overtaking, with the own ship (OS). Our algorithm, however, focuses on predicting the intention of NSs that are not posing any risk of collision to the OS at the moment. The contributions of this paper are:

(1) A scenario-based model predictive control approach for inland waterway ships to avoid collision and grounding hazards.
(2) A situation-based intention prediction algorithm that helps the own ship to be aware of potential course changes of NSs.

The rest of this paper is organized as follows. The notations and assumptions are introduced in Section 2. Section 3 presents the details of our proposed collision avoidance algorithm. The algorithm's performance is then evaluated through simulation studies in Section 4, and conclusions and future works are given in Section 5.

2. PRELIMINARIES

To begin with, let us use the waterway coordinate frame $\{\eta\}$ to define the position of OS and NS (see Fig. 1). The x coordinate is parallel with the waterway and connects waypoints, the y coordinate is perpendicular to the bank, and the origin and nominal waypoints are placed in the middle of the waterway. We use the term "own ship" (OS) for the ship that is under our control, and the NS for all other ships that operate near the OS. The 2-D position of the OS at time step k is denoted by $\boldsymbol{p}^k = \left[p_x^k, p_y^k\right]$, similarly the position and velocity of NS with index i is

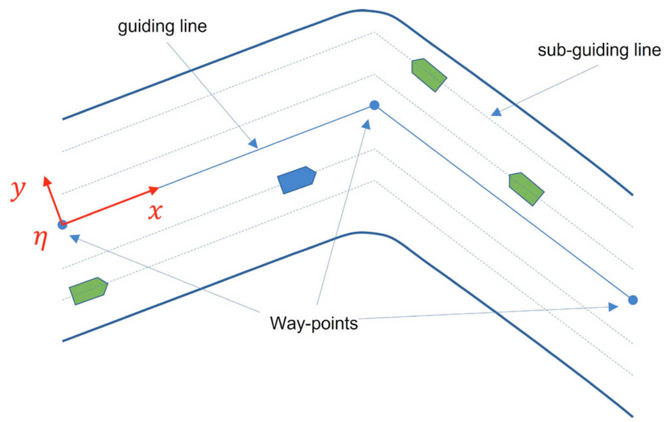


Fig. 1. Narrow channel with road coordinate: OS is in blue and NS are in green.

$\boldsymbol{p}_i^k = \left[p_{i,x}^k, p_{i,y}^k\right], \boldsymbol{v}_i^k = \left[v_{i,x}^k, v_{i,y}^k\right]$. Besides, the set of all NSs is denoted by $\mathcal{M}$.

It is a fact that most of the ships that sail in rivers/channels (except for ferries) either want to sail upstream or downstream. Therefore, we assume that all ships sailing in the same river/channel as the OS have the same intention as the OS, i.e., the intention of sailing along the waterway. A detailed method of intention modelling for autonomous ships can be founded in Rothmund et al. (2022). Without loss of generality, we further assume that all ships sailing along the waterway have the same waypoints. We define the guiding line as the line that connects waypoints; the sub-guiding line is a parallel line with the guiding line, representing the planned route of each ship.

Our collision avoidance algorithm is developed based on the assumption of the availability the following information:

- The NS information including: position and velocity.
- Mapped hazards from an electronic map.

3. COLLISION AVOIDANCE FOR INLAND SHIPS

This section proposes a scenario-based model predictive control (SB-MPC) approach for ships that sail in narrow waterways such as rivers or channels. The control system structure is assumed to be similar to Johansen et al. (2016), including three subsystems: autopilot, line-of-sight (LOS) guidance, and collision avoidance (COLAV). In the original SB-MPC, the algorithm adds an angle χ_{ca} to the desired course angle χ_d and modifies forward speed with a factor U_{ca}, to guide the OS to avoid collisions. Following this method, the OS can avoid collision and simultaneously sail toward the next waypoint. However, strictly following the guiding line is not necessary in the case of IWT. Therefore, instead of adding a collision angle, χ_{ca}, our proposed COLAV algorithm adds an offset value, y_{ca} to the cross-track error y_e (see Fig. 2). This modification allows the OS to keep the course parallel with the guiding line while avoiding collisions. Without loss of generalization, the algorithm are developed for straight waterway cases. Our algorithm can also be applied to the curved waterways by introducing a coordinate transformation from inertial frame to Frenet frame as in Fossen (2011).

3.1 Own ship trajectory prediction

We present a kinematic model to describe the OS's motion with respect to the $\{\eta\}$ coordinate frame with the assumption there is a motion controller that can compensate for all the disturbances, e.g., wind, flow stream, and model inaccuracy in ship dynamics. The kinematic model is based on the setpoint filter model of Lutz and Gilles (2010), as follows:

$$
\begin{aligned}
p_x^k &= p_x^{k-1} + U_{ca}U_d\cos(\chi^k)\Delta T,\\
p_y^k &= p_y^{k-1} + U_{ca}U_d\sin(\chi^k)\Delta T,\\
\chi^k &= \chi^{k-1} + \frac{1}{T_1}(\chi_d - \chi^{k-1}),\\
\chi_d &= \chi_{max}\tanh(K_e y_e^k),\\
y_e^k &= (y_{ca} + y_0) - p_y^{k-1},
\end{aligned} \tag{1}
$$

where $\chi^k, \chi_d, \chi_{max}$ are, respectively, the course angle, desired course angle at time $t = k\Delta T$ and the maximum steering angle of OS; U_d is the predefined nominal surge speed of the OS. Moreover, the control action $\boldsymbol{u}^k = [U_{ca}, y_{ca}]$ denotes the COLAV speed coefficient and sub-guiding line; T_1 and K_e are positive constants, and y_0 is the desired sub-guiding line from time step $k-1$.

3.2 Neighbor-ship trajectory prediction

We propose a two-stage trajectory prediction (2-STP) algorithm to predict the motion of NS i, which includes an intention and a position prediction. At the beginning of the prediction process at time step k, the intention prediction (IP) runs once to predict the future sub-guiding line of NS based on predefined rules presented below. The predicted intention is applied to the position prediction in the COLAV algorithm, utilizing a simple kinematic model to estimate the future position of NS i.

Intention prediction: In this step, we predict the intention change of NS i based on these assumptions:

(a) The NS keeps its course (speed and road line) if there is no potential collision risk ahead.
(b) The NS has to take action if there is a collision threat in its current sub-guiding line.
(c) The NS actions is expect to follow the traffic rules
(d) The NS prefers choosing the closest sub-guiding line if it faces an obstacle.

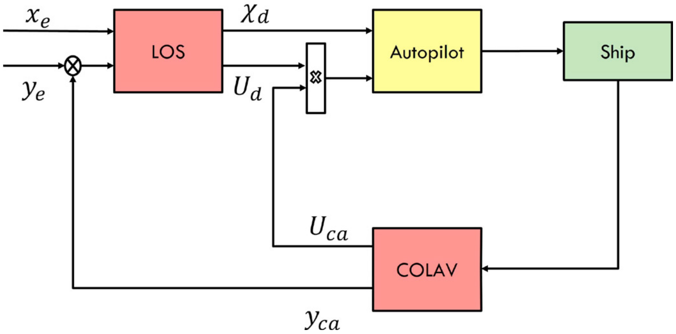


Fig. 2. Proposed collision avoidance algorithm: *the along-track and cross-track errors are x_e, and y_e, while U_d and χ_d are desired speed and course angle.*

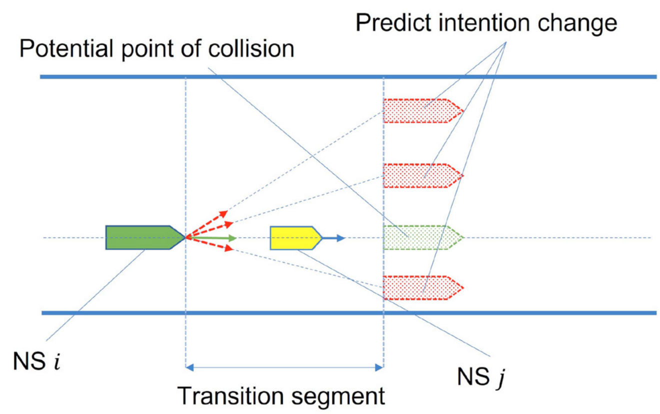


Fig. 3. **Intention prediction:** The green and yellow ships sail over the same sub-guiding line in the same direction (blue vectors), but the green ship is faster than the yellow ship. There is a potential collision between the two ships, with a potential collision point dotted blue if no action is taken. The intention prediction of the OS then predicts the possible velocity change (red dash line vector) and corresponding position of NS i.

Therefore, OS only applies the intention prediction for each NS that has a potential collision threat over its prediction horizon (see Fig. 3).

The detailed algorithm is present in Algorithm 1. Firstly, IP searches for the closest collision threat of the NS i (steps 2 - 8) and the distance in the x-axis from the NS i to the collision point, γ_i. The collision threat can either be other "close-NS" or grounding. In here, a NS j is a "close-NS" of NS i if $|p_{i,y}^k - p_{j,y}^k| < \epsilon_y$ where ϵ_y is a positive constant. γ_i is initialized in step 2, where it is the distance to the closest grounding hazard in the current sub-guiding line, denoted by $g(p_{i,y}^k)$, or the maximum distance that ship i can sail over the prediction horizon, i.e., T_h. For "close-NS" j of NS i, we calculate d_{ca}^j: the distance in the x-axis to from NS i to the collision point with NS j, i.e., $p_{i,x}^k = p_{j,x}^k$. If $d_{ca}^j < \gamma_i$, we update γ_i, then continue with other "close-NS". When γ_i is finally computed, if there is a collision threat within the prediction horion ($\gamma_i < |v_{i,x}T_h|$), the algorithm will evaluated the nearby sub-guiding lines $c_{i,y} = p_{i,y}^k + y_m$, where $y_m \in \mathcal{C}$ is the action and $\mathcal{C}$ is the set of actions (steps 9 - 15). The action evaluation is based on the condition of the neighboring sub-guiding line,the distance from the current sub-guiding line, and the compliance with the Convention on the International Regulations for Preventing Collision at Sea (COLREGs). The certainty value, P_m corresponding with action y_m, is updated at step 13. This parameter represents how certainly the scenario will happen, with a higher value meaning a higher chance of happening. Step 13 also guarantees that $P \in [0,1]\ \forall\ \alpha_m \geq 0$. The following rules calculate the cost of the event, α_m, in step 12:

(1) The cost of changing sub-guiding line from $p_{i,y}^k$ to $p_{i,y}^k + y_m$ is $r_y||y_m||$.
(2) If the chosen sub-guiding line is not available at $\boldsymbol{p}_i^{ca} = [c_{i,x}, c_{i,y}]^T$, i.e., the sub-guiding line lies on the area the NS cannot sail, then $\alpha_m = 1$.

(3) If the neighboring sub-guiding line has obstacles in the "transition segment" (the line segment from $p_{i,x}^k$ to $c_{i,x}$), then each obstacle adds r_{ob} to α_m. This rule means that the ship is likely not to choose a congested sub-guiding line.
(4) Violating the COLREGS (rule 14) gives an additional cost of r_c percent of the cost for the normal action. This means that the action that violates a certain COLREGS rule can happen but with lower possibility.

Algorithm 1 Intention prediction

for all $i, j \in \mathcal{M}, i \neq j, k \leq T_h/\Delta T, k \in \mathbb{R}^+$ **do**
  Set the closest threat distance equal to the grounding hazard $\gamma_i = g(p_{i,y}^k)$ (if there is no grounding hazard then $\gamma_i = |v_{i,x}T_h|$)
  if $|p_{i,y}^k - p_{j,y}^k| < \epsilon_y$ **then**
    $d_{ca}^j = |v_{i,x}\frac{p_{i,x}^k - p_{j,x}^k}{v_{i,x} - v_{j,x}}|$
    if $\gamma_i > d_{ca}^j$ **then**
      $\gamma_i = d_{ca}^j$
    end if
  end if
  if $\gamma_i < |v_{i,x}T_h|$ **then**
    for $y_m \in \mathcal{C}$ **do**
      $c_{i,x} = p_{i,x}^k + sgn(v_{i,x})\gamma_i$; $c_{i,y} = p_{i,y}^k + y_m$; $\boldsymbol{p}_i^{ca} = [c_{i,x}, c_{i,y}]^T$
      calculate the cost α_m of sailing to $\boldsymbol{p}_i^{ca}$
      $P_m = 1 - \min(\alpha_m, 1))$
    end for
  end if
end for

Position prediction: This stage calculates the position of NS i at different time steps. These positions will be used later in the "Collision risk evaluation" step. The position prediction uses the constant velocity kinematic model, where the current velocity is combined as follows with the prediction velocity vectors from the intention prediction:

$$\begin{cases} p_{i,x}^k &= p_{i,x}^{k-1} + v_{i,x}^k T_p, \\ p_{i,y}^k &= p_{i,y}^{k-1} + v_{i,y}^k T_p, \end{cases} \tag{2}$$

where T_p is the prediction time step.

3.3 COLREGS compliance

The following behaviors are applied to comply with two main COLREGS rules:

(1) Rule 13 (Being overtaken): OS stand on while being overtaken by the obstacle coming from her abaft, except at the emergency distance d_x^s.
(2) Rule 14 (Head-on): OS changes its course to the starboard side when facing a head-on situation.

The OS, in most of case, will follow these COLREGS rules. However, the OS could violate COLREGS rules if following these rules lead to unavoidable collisions. The COLREGS compliance cost of the OS with NS i is defined as:

$$\mu_i = \sum_{m=1}^{N} P_m K_\mu (R_{13} + R_{14}), \tag{3}$$

in which R_{13}, R_{14} are binary variables equal to 1 if OS violates the COLREGS rules 13 or 14, respectively, with respect to NS i; and N is the number of selected cases from IP. We can use one or several cases with the highest certainty value for the position prediction from the IP. It is worth noting that: increasing the number of chosen cases, on the one hand, increases the situational awareness of the OS, but on the other hand, causes unnecessary changing of sub-guiding lines due to "false alarms".

3.4 Collision risk evaluation

The collision risk factor of OS with NS i is defined as:

$$R_i(t) = \begin{cases} F(t) & \text{, if } \delta x_{i,m}(t) < d_x^s \text{ AND } \delta y_{i,m}(t) < d_y^s \\ 0 & \text{, otherwise} \end{cases} \tag{4}$$

where $F(t) = \sum_{m=1}^{N} \frac{K_{ca}P_m}{\|t-t_0\|} exp\left(-\frac{(\delta x_{i,m}(t))^2}{\alpha_x} - \frac{(\delta y_{i,m}(t))^2}{\alpha_y}\right)$; $\delta x_{i,m}(t)$, $\delta y_{i,m}(t)$ are predicted distances between OS and the case m (from IP) of NS i at time t in x and y axis, respectively. t_0 is the current time, and K_{ca}, α_i, d_i^s ($i \in \{x, y\}$) are predefined constants based on safety criteria.

Then the cost function at time t_0 is:

$$\mathcal{J}(t_0, \mathbf{u}) = \max_{i \in \mathcal{M}} \max_{t \in \mathcal{D}(t_0)} (R_i(t) + \mu_i(t)) + K_y y_{ca}^2 + K_U (1 - U_{ca})^2, \tag{5}$$

where $\mathcal{D}(t_0)$ is the set of sample time within prediction horizon; μ_i and are $R_i(t)$ calculated follows (3) and (4), respectively. This cost function only penalizes when the ship changes the sub-guiding line or speed. On the other hand, it allows the OS to sail along any sub-guiding line with no collision threat and no COLREGS violation instead of strictly following the guiding line.

3.5 SB-MPC for the inland waterway ship

The set of control behavior, $\mathcal{U}$, for the SB-MPC is:

- Guiding line offset y_{ca}: $-6\delta_y$, $-5\delta_y$, $-4\delta_y$, $-3\delta_y$, $-2\delta_y$, $-\delta_y$, 0, δ_y, $2\delta_y$, $3\delta_y$, $4\delta_y$, $5\delta_y$, $6\delta_y$. Where δ_y is a design parameter, e.g., $\delta_y = 10m$.
- Speed modification factor U_{ca}: 0, 0.5, 1.

The COLAV problem is solved by choosing an optimize control action $\boldsymbol{u}^* \in \mathcal{U}$ that minimizes the cost function $\mathcal{J}$:

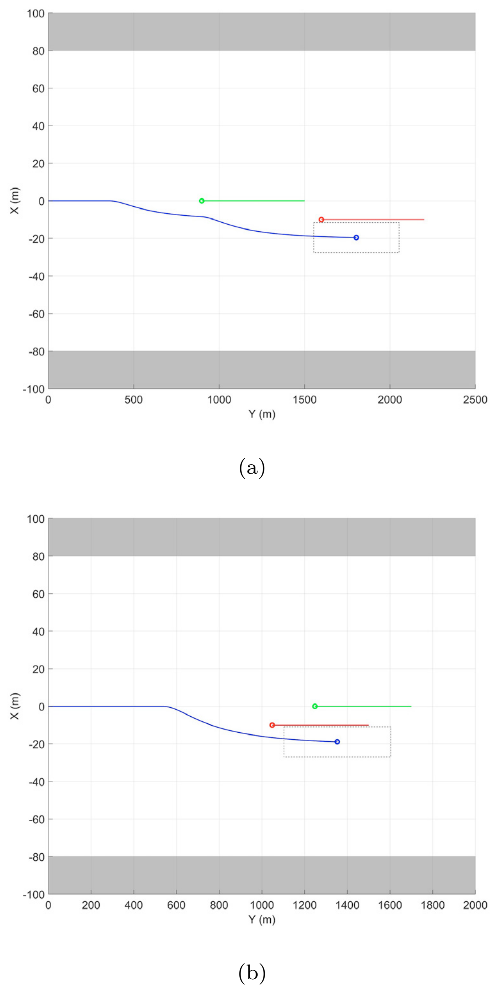
$$\boldsymbol{u}^* = arg \min_{\boldsymbol{u} \in \mathcal{U}} \mathcal{J}(t_0, \boldsymbol{u}), \tag{6}$$

where $\mathcal{J}$ is given in (5). One can modify the control set $\mathcal{U}$ to make it suitable for a specific ship and waterways. Especially the guiding line offset should be chosen carefully to allow the controller to avoid a potential collision.

4. SIMULATION EXPERIMENTS

In this section, we present simulation experiments to illustrate the performance of our proposed algorithm in various traffic scenarios. The proposed algorithm is evaluated for two cases:

(1) Case 1 (Simple): OS overtaking or head-on with single or multiple NSs when only OS takes action.
(2) Case 2 (Complex): OS overtaking or head-on with multiple NSs that also take action at the same time.



(a)

(b)

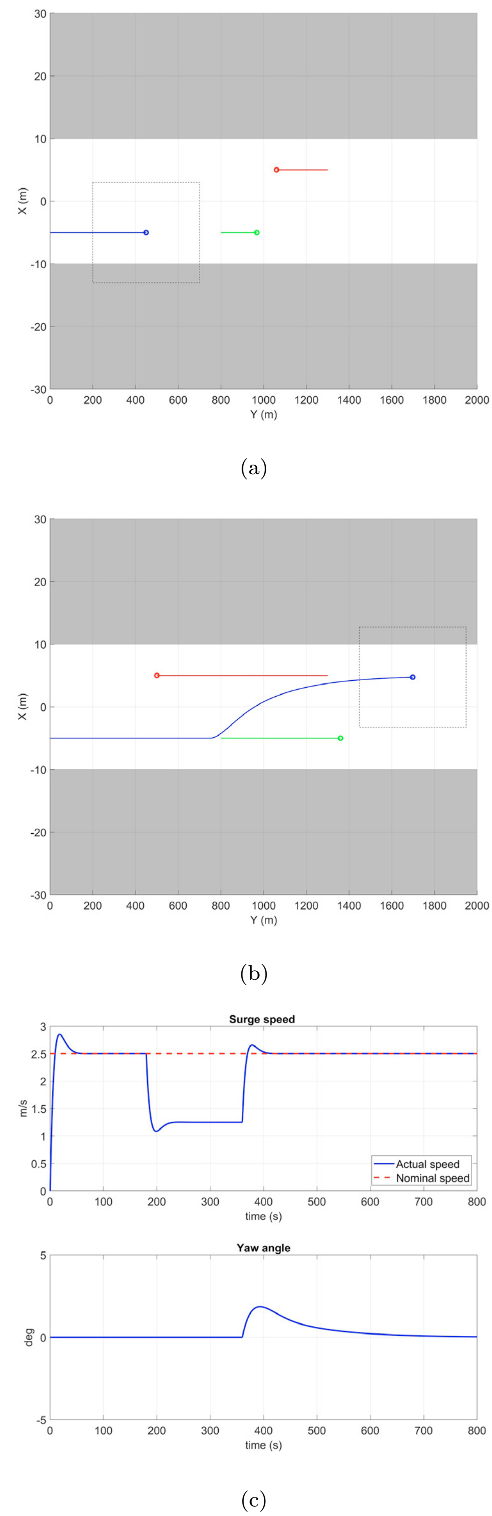
Fig. 4. Head-on scenarios with multiple NSs.

The control parameters for the OS are the same in all simulations. The safety parameters are chosen that d_x^s is five times larger than the ship's length, and d_y^s is dependent on the ship's maneuverability but at least one time larger than the ship's beam. Therefore, for the ship model with $51.5m$ length and $8.6m$ beam, we set $d_x^s = 250m$, $d_y^s = 10m$. The black dash rectangle shows the aware safety area of the OS. In the result figures, the white area represents the sailable area, while the gray area is where the ship cannot sail. The blue circle illustrates the OS, and NS are red and green circles. The simulation scenarios are set up to illustrate our proposed algorithms' performance.

4.1 Simple scenarios

In this case, the OS encounters constant velocity NSs and only OS takes action to resolve the situation. This test aims to verify the rules compliance ability of the algorithm in standard head-on and overtaking scenarios.

Fig. 4 shows the head-on situation where the OS faces multiple NS that sail in the opposite direction. The OS quickly resolves the situation with minimum effort and, at the same time, compliance with COLREGS. In a more complex case, as shown in Fig. 5, the OS attempts to overtake the green NS while avoiding the red NS coming from the opposite direction. The solution is to slow down, and wait for the red NS to pass (see Fig. 5c), then to change the sub-guiding line. Overall, our algorithm can handle these collision avoidance cases while maintaining the reference speed.



(a)

(b)

(c)

Fig. 5. Overtaking in narrow channel: The blue OS attempts to overtake green NS while avoiding collision with red NS

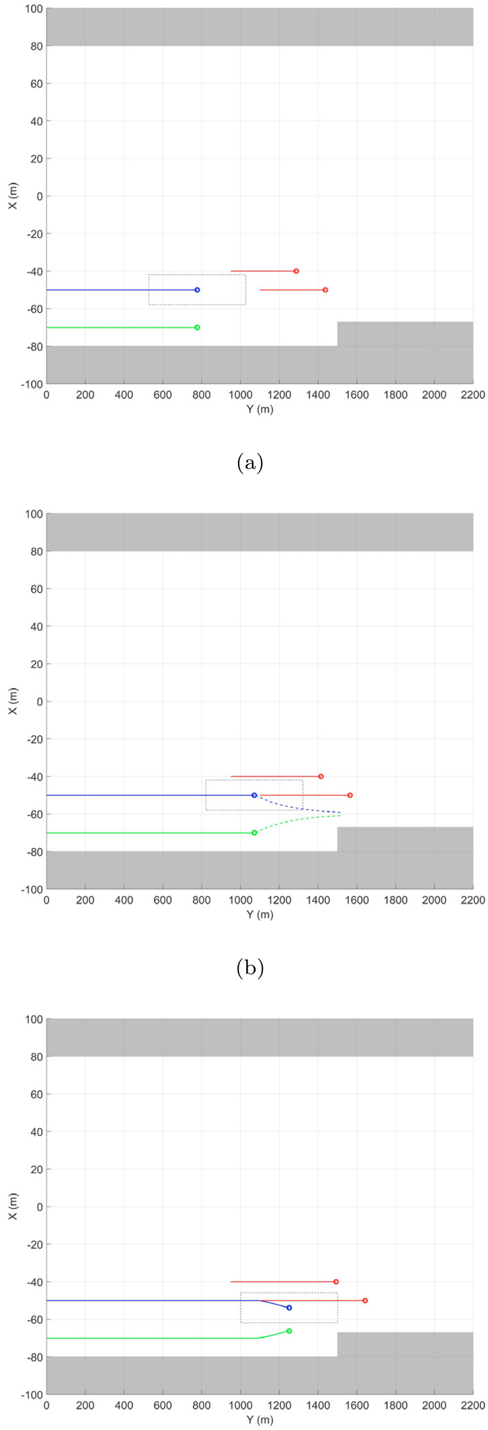


Fig. 6. Own ship encounter a complex scenarios without long term prediction: (a) The blue OS attempts to overtake two red NS, and is not aware of green NS; (b), (c) The decisions of blue OS and green NS could lead to collision.

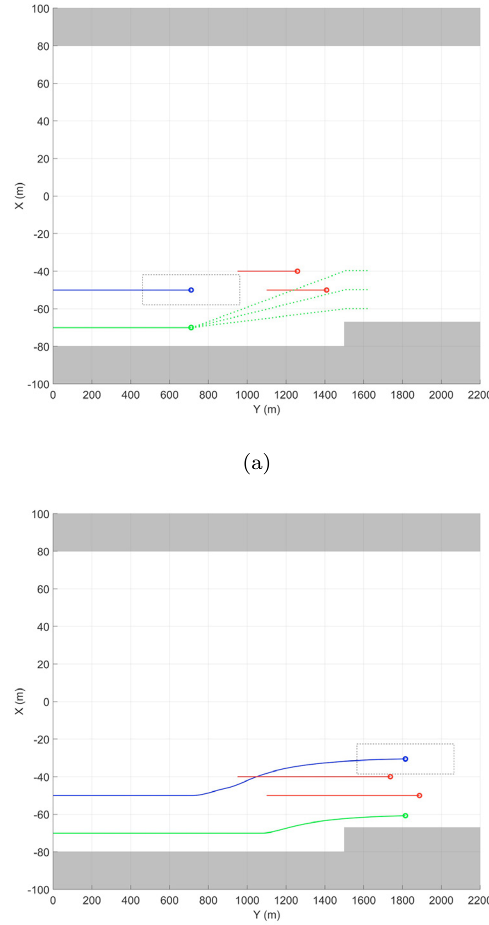


Fig. 7. Own ship encounter a complex scenarios with long term prediction: (a) The blue OS is aware that green NS will change its course; (b) the OS chooses sub-guiding line y=-30 to avoid collision with green NS.

4.2 Complex scenario

It is commonly assumed in the literature that only OS makes decisions during the encounter process. However, when the OS can detect a potential collision risk, the NS on the other side could also execute some action to avoid collisions. In some scenarios that involve several ships, the simultaneous decision from multiple ships can sometimes lead to an increased collision risk. In this section, we investigate the performance of the proposed algorithm in a complex scenario where NSs simultaneously make decisions to avoid a collision.

In Fig. 6a, the OS attempts to overtake two red NS. The green NS, in this case, is not a collision threat to the OS since it sails in parallel and further away than the safety distance of the OS. Without the intention prediction, the sub-guiding line $y = -60m$ is chosen for the OS (the blue dash line in Fig. 6b). However, because the sub-guiding line of the green NS is blocked at $x = 1500m$, it also has to change its sub-guiding line (the green dash line in Fig. 6b). Consequently, the decisions of the two ships could lead to a collision (Fig. 6c). With the help of the 2-STP, the OS is aware that the green NS will have to change its sub-guiding line (the green dotted lines in Fig. 7a). With this information, the sub-guiding line $y = -30m$ is the better choice (Fig. 7b), and all ships safety leave the situation.

5. CONCLUSION & FUTURE RESEARCH

In this paper, we proposed a collision avoidance algorithm for autonomous ships in inland waterways. The algorithm addresses the complex case of IWT, where multiple ships simultaneously make decisions. We integrate in the COLAV algorithm the 2-STP, which helps the OS to be aware of possible collision risks caused by the intention change of NSs. The final collision avoidance decision is made using the SB-MPC, which is modified to adapt to IWT scenarios. In future research, we aim to combine the 2-STP with the intention exchange/negotiation system to develop a hybrid solution that can work in variable cases, when ship can also actively exchange information among another.

REFERENCES

Akdağ, M., Solnør, P., and Johansen, T.A. (2022). Collaborative collision avoidance for maritime autonomous surface ships: A review. *Ocean Engineering*, 250, 110920.

Chen, C.Y., Delefortrie, G., and Lataire, E. (2021a). Effects of water depth and speed on ship motion control from medium deep to very shallow water. *Ocean Engineering*, 231.

Chen, C.Y., Verwilligen, J., Mansuy, M., Eloot, K., Lataire, E., and Delefortrie, G. (2021b). Tracking controller for ship manoeuvring in a shallow or confined fairway: Design, comparison and application. *Applied Ocean Research*, 115.

Chen, L.Y., Huang, Y.M., Zheng, H.R., Hopman, H., and Negenborn, R. (2020). Cooperative multi-vessel systems in urban waterway networks. *IEEE Transactions on Intelligent Transportation Systems*, 21(8), 3294–3307.

Du, Z., Negenborn, R.R., and Reppa, V. (2022). Colregs-compliant collision avoidance for physically coupled multi-vessel systems with distributed mpc. *Ocean Engineering*, 260.

Fang, M.C., Tsai, K.Y., and Fang, C.C. (2018). A simplified simulation model of ship navigation for safety and collision avoidance in heavy traffic areas. *Journal of Navigation*, 71(4), 837–860.

Fossen, T.I. (2011). *Handbook of marine craft hydrodynamics and motion control*. John Wiley & Sons.

He, Y.Y., Mou, J.M., Chen, L.Y., Zeng, Q.S., Chen, P.F., and Zhang, S. (2021). Survey on hydrodynamic effects on cooperative control of maritime autonomous surface ships. *Ocean Engineering*, 235.

Helling, S., Lutz, M., and Meurer, T. (2020). Flatness-based MPC for underactuated surface vessels in confined areas. *IFAC Papersonline*, 53(2), 14686–14691. doi: 10.1016/j.ifacol.2020.12.1831.

Hexeberg, S., Flåten, A.L., Eriksen, B.O.H., and Brekke, E.F. (2017). Ais-based vessel trajectory prediction. In *2017 20th International Conference on Information Fusion (Fusion)*, 1–8.

Huang, Y.M., Chen, L.Y., Chen, P.F., Negenborn, R.R., and van Gelder, P.H.A.J.M. (2020). Ship collision avoidance methods: State-of-the-art. *Safety Science*, 121, 451–473.

Johansen, T.A., Perez, T., and Cristofaro, A. (2016). Ship collision avoidance and colregs compliance using simulation-based control behavior selection with predictive hazard assessment. *IEEE Transactions on Intelligent Transportation Systems*, 17(12), 3407–3422.

Lutz, A. and Gilles, E.D. (2010). An automatic collision detection and avoidance module for inland navigation. *IFAC Proceedings Volumes*, 43(20), 254–259.

Mahini, F., DiWilliams, L., Burke, K., and Ashrafiuon, H. (2013). An experimental setup for autonomous operation of surface vessels in rough seas. *Robotica*, 31(5), 703–715.

Rong, H., Teixeira, A.P., and Soares, C.G. (2019). Ship trajectory uncertainty prediction based on a gaussian process model. *Ocean Engineering*, 182, 499–511.

Rothmund, S.V., Tengesdal, T., Brekke, E.F., and Johansen, T.A. (2022). Intention modeling and inference for autonomous collision avoidance at sea. *Ocean Engineering*, 266. doi:ARTN11308010.1016/j.oceaneng.2022.113080.

Scheepens, R., van de Wetering, H., and van Wijk, J.J. (2014). Contour based visualization of vessel movement predictions. *International Journal of Geographical Information Science*, 28(5), 891–909.

Shah, B.C., Svec, P., Bertaska, I.R., Sinisterra, A.J., Klinger, W., von Ellenrieder, K., Dhanak, M., and Gupta, S.K. (2016). Resolution-adaptive risk-aware trajectory planning for surface vehicles operating in congested civilian traffic. *Autonomous Robots*, 40(7), 1139–1163.

Song, R.T. and Li, B. (2021). Surrounding vehicles' lane change maneuver prediction and detection for intelligent vehicles: A comprehensive review. *IEEE Transactions on Intelligent Transportation Systems*, 23(7), 6046–6062.

Tam, C. and Bucknall, R. (2013). Cooperative path planning algorithm for marine surface vessels. *Ocean Engineering*, 57, 25–33.

Tengesdal, T., Brekke, E.F., and Johansen, T.A. (2020). On collision risk assessment for autonomous ships using scenario-based MPC. *IFAC Papersonline*, 53(2), 14509–14516.

Tengesdal, T., Johansen, T.A., Grande, T.D., and Blindheim, S. (2022). Ship collision avoidance and anti grounding using parallelized cost evaluation in probabilistic scenario-based model predictive control. *IEEE Access*, 10, 111650–111664.

Vantorre, Marc and Laforce, E and Clayeyssens, P (1997). Development of an autopilot for fast-time simulation in confined waterways. In Wilson, PA (ed.), *Eleventh ship control systems symposyum*, volume 1, 203–217. Computational mechanics publications LTD.

Zhang, G.Y., Wang, Y., Liu, J., Cai, W., and Wang, H.B. (2022). Collision-avoidance decision system for inland ships based on velocity obstacle algorithms. *Journal of Marine Science and Engineering*, 10(6), 814.

Zheng, H.R., Negenborn, R.R., and Lodewijks, G. (2016). Predictive path following with arrival time awareness for waterborne agvs. *Transportation Research Part C-Emerging Technologies*, 70, 214–237.

Zheng, H.R., Negenborn, R.R., and Lodewijks, G. (2017). Fast admm for distributed model predictive control of cooperative waterborne agvs. *Ieee Transactions on Control Systems Technology*, 25(4), 1406–1413.