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IFAC PapersOnLine 55-31 (2022) 307–312

Scenario-Based Model Predictive Control with Several Steps for COLREGS Compliant Ship Collision Avoidance

I. B. Hagen * D. K. M. Kufoalor * T. A. Johansen * E. F. Brekke *

* Center for Autonomous Marine Operations and Systems (NTNU-AMOS), Department of Engineering Cybernetics, Norwegian University of Science and Technology, Trondheim, Norway

Abstract: The main question investigated is whether additional decision steps can improve vessel behavior produced by the collision avoidance method scenario based model predictive control (SBMPC). The method, which functions by predicting alternative paths resulting from a finite number of alternative control behaviors, then selecting which behavior to apply by use of a cost function, was originally formulated to allow switching between several behaviors on the prediction horizon. However, current implementations have been limited to a single control step. To compare the single-step and multi-step SBMPC, a simulation study was performed, where different configurations for the number, positioning and possible control actions were tested. In the course of the simulation study it became clear that identifying situations producing a significant difference between the two methods was difficult to identify and the multi-step SBMPC led to only minor improvements in very few scenarios. Nevertheless, multi-step decisions can be visualized to give better situational awareness, and also have additional benefits with other trajectory parameterizations and less uncertain predictions of other ship trajectories.

Keywords: Autonomous Surface Vehicles, Collision Avoidance, COLREGS, Model Predictive Control

1. INTRODUCTION

Anti-collision control in compliance with the main COLREGS traffic rules at sea is essential in autonomous navigation systems that are required to realize the vision of autonomous ships. This is an active area of research, where several algorithms have been proposed in the literature. The research presented in this paper is designed to study in more depth the so-called Scenario-Based Model Predictive Control (SBMPC) approach that was introduced in Johansen et al. (2016), and we only refer to Vagale et al. (2021) for a comprehensive review of alternative methods.

The SBMPC method considers a prediction of alternative trajectories for other ships together with a simulation-based prediction of alternative trajectories for the own ship. Scenarios are generated based on the available information about other ships behavior and the alternative control actions that can be taken by own ship, i.e. change in course or speed. By considering a finite number of scenarios, the optimal own ship control action is selected by minimizing a cost function that penalizes collision risk, COLREGS violation and deviation from the pre-planned nominal path. Optimality is evaluated on a finite time horizon into the future, where the length of this horizon corresponds to a typical encounter between ships, e.g. 10 minutes. The method has been tested in field trials in Kufoalor et al. (2020) and Kufoalor et al. (2019), and several extensions have been studied, e.g. Tengesdal et al. (2020, 2022); Akdag et al. (2022).

Although the original SBMPC paper Johansen et al. (2016) describes that the Model Predictive Control (MPC) algorithm can switch between several control policies on the horizon, e.g. different speeds or course offsets, the current implementations are limited to single-step SBMPC Hagen et al. (2018), which is motivated by test results showing that a single-step approach is sufficient to achieve International Regulations for Preventing Collisions at Sea (COLREGS) compliance and safety in typical encounters. The main reason for this is likely that the safety cost is designed with an explicit time-dependent discounting factor that means that the closest collision risks are prioritized before more distant collision risks. Since the SBMPC re-evaluates the cost periodically based on updated information, this strategy is found to be successful also in multi-ship encounters, Kufoalor et al. (2020, 2019). We note that so-called move-blocking strategies that lead to control input parameterizations with a lower number of decision steps are common in MPC in order to reduce computational complexity and increase robustness, Gondhalekar and ichi Imura (2010); Cagienard et al. (2007) and it is common in industrial process control with MPC is

⋆ This work was primarily funded and supported by Kongsberg Maritime as part of the University Technology Center. It was also partly funded by the Research Council of Norway through the Center of Excellence on Autonomous Marine Operations and Systems (NTNU AMOS), grant number 223254.

D. K. M. Kufoalo is currently with Maritime Robotics.
Corresponding author e-mail: inger.b.hagen@ntnu.no

10.1016/j.ifacol.2022.10.447

implemented with only a single decision step, Qin and Badgwell (2003).

In this paper we study how a multi-step SBMPC compares to a single-step SBMPC. This is motivated by the following:

- Multiple decision steps provides additional degrees of freedom for the control action on the horizon, that is in general expected to improve efficiency in utilization of the available space, time, energy and resources.
- There could be complex situations, in particular multi-ship encounters and grounding hazards, where more complex maneuvers are needed and it could be important to plan more pro-actively.
- It is helpful to visualize the complete plan to the helmsman, including the explicit plan for return to the original planned path, in order to increase trust and situational awareness. With a one-stage SBMPC the implicit assumption is that other ships that are further away, and the return to original path, will be dealt with later, which may not always provide sufficient trust.

These advantages must be weighted against increased computational complexity and evaluated also in the context of robustness to uncertainty about other ships' behaviors into the future.

The remainder of this paper is structured as follows: Section 2 gives an overview of the original SBMPC method and a description of the proposed modifications. The setup for the simulation study is explained in section 3, followed by a presentation of results in section 4 and a discussion around these in section 5.

2. COLREGS COMPLIANT COLLISION AVOIDANCE

This section describes the collision avoidance methods employed in the later simulations. First, a brief overview is given of the previous work on the SBMPC method, for more details see Johansen et al. (2016) and Hagen et al. (2018), then follows a more detailed explanation of the proposed extensions.

2.1 SBMPC

In essence, the SBMPC method seeks to identify the minimal maneuver producing a collision-free and safe trajectory. This is done by making a prediction of the future trajectory for each obstacle, along with a prediction for the ownship's trajectory for each alternative control behavior enumerated by the index, k, given by the finite set K. Each of the ownship's trajectories is assigned a cost and the control behavior incurring the lowest cost is applied to the vessel. Identifying this control behavior is done by solving the following optimization problem at the current time, t_0:

$$k^*(t_0) = \arg\min_k \mathcal{H}^k(t_0), \tag{1}$$

where the cost function calculating the cost for each control behavior is defined as

$$\mathcal{H}^k(t_0) = \max_i \max_{t\in\mathcal{T}(t_0)} \mathcal{H}_i^k(t) + f(u_m^k, \chi_m^k). \tag{2}$$

The function f in the above equation denotes the cost of maneuvering efforts incurred by the control behavior, and is defined by modifications to course angle (χ_m^k) and speed (u_m^k), while the cost with regards to each obstacle (i) is given by

$$\mathcal{H}_i^k(t) = c_i(u_m^k, \chi_m^k, t) + \mu_i(u_m^k, \chi_m^k, t) + \tau_i(u_m^k, \chi_m^k, t). \tag{3}$$

The function c_i denotes the cost of collision risk, μ_i the cost for violating the COLREGS, and τ_i is a cost on transitions between situation types, e.g., a maneuver that turns an overtaking into a crossing. These three functions are time dependent and their cost is calculated based on the predicted trajectories for each element in the set $\mathcal{T}(t_0) = \{t_0, t_0 + T_s, \ldots, t_0 + T\}$, where T_s is the sampling period and T is the prediction horizon. Note that the function c_i includes the mentioned discounting of future events though a factor $1/(t - t_0)^p$, where $p \geq 1/2$ is an exponent. Grounding risks can also be included in a similar manner.

The cost function $\mathcal{H}^k(t_0)$ thus calculates the cost for selecting control behavior k at time t_0. The stage cost at time $t \in \mathcal{T}(t_0)$ is based on the predicted state of the autonomous surface vehicle (ASV) and each obstacle i. For the ASV, the trajectory is predicted by simulation using a 3-degrees of freedom (DOF) model:

$$\begin{aligned} \dot{\boldsymbol{\eta}} &= \boldsymbol{R}(\psi)\boldsymbol{v}, \\ \boldsymbol{M}\dot{\boldsymbol{v}} + \boldsymbol{C}(\boldsymbol{v})\boldsymbol{v} + \boldsymbol{D}(\boldsymbol{v})\boldsymbol{v} &= \boldsymbol{\tau}_u, \end{aligned} \tag{4}$$

where position and heading in the Earth-fixed coordinate frame is given by $\boldsymbol{\eta} = (x, y, \psi)$ and surge, sway and yaw velocities in the body-fixed frame by $\boldsymbol{v} = (v_x, v_y, r)$. In the above equation, $\boldsymbol{R}(\psi)$ represents a rotation matrix and $\boldsymbol{M}$, $\boldsymbol{C}$ and $\boldsymbol{D}$ are the mass, Coriolis and damping matrices. The force vector $\boldsymbol{\tau}_u$ is produced by the propulsion and steering system. An autopilot takes as input command values for course and speed, which for each control behavior is given by $\chi_c(t) = \chi_r(t) + \chi_m^k$ and $u_c(t) = u_r(t) \cdot u_m^k$, where χ_r and u_r are the reference values chosen to follow the pre-planned path. The time dependency of the reference and command values are due to the inclusion of a guidance strategy, which is necessary to obtain sufficient accuracy in the predictions. The method employed in this work is the line-of-sight (LOS) guidance strategy.

For each obstacle i, a kinematic model is used:

$$\dot{\boldsymbol{\eta}}_i = \boldsymbol{\eta}_i = (x_i, y_i), \;\; \boldsymbol{v}_i = (v_{x,i}, v_{y,i}), \tag{5}$$

where the position and velocity coordinates are in the Earth-fixed coordinate frame. This assumes that the obstacle will continue on a straight-line trajectory. This is suitable when the obstacle is deemed to be the stand on vessel. In cases where the obstacle is required to give way a more complex model could predict more accurately the obstacle's intended path, but this is outside the scope of this paper.

The set K of alternative control behaviors employed is given by:

- For course: $\chi_m^k \in \{-90°, -75°, -60°, -45°, -30°, -15°, 0°, 15°, 30°, 45°, 60°, 75°, 90°\}$
- For speed: $u_m^k \in \{1, 0.5, 0\}$, which signifies 'keep speed', 'slow down' and 'stop'.

The combination of these gives $|K| = 13{\cdot}3 = 39$ alternative control behaviors. The predicted paths for these control behaviors in a head-on situation using LOS guidance is

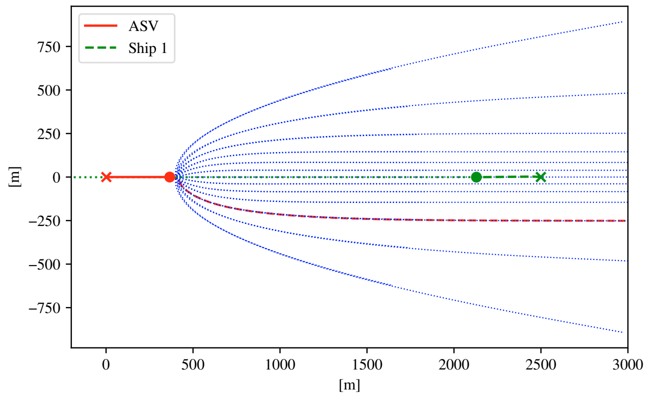


Fig. 1. SBMPC path predictions: ASV alternative paths (····), ASV optimal path (– – –) and obstacle path (····).

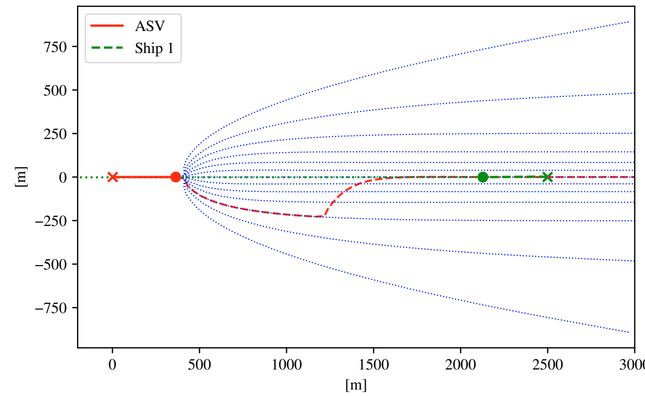


Fig. 2. Multi-step SBMPC return-to-path predictions: ASV alternative paths (····), ASV optimal path (– – –) and obstacle path (····).

shown in Figure 1. The curved appearance of the paths is due to predicted changes in the course reference (χ_r) which depends on the ASV's position.

2.2 Multi-step SBMPC

The SBMPC algorithm contains a single decision point at the present time $t = t_0$ for the ASV's predicted paths, meaning that only one course and/or speed maneuver is planned on the horizon. In the multi-step SBMPC, additional decision points within the prediction horizon allow for multiple planned maneuvers.

To keep the algorithm's runtime down, it is desirable to investigate whether only a limited increase in the number of possible trajectories is sufficient to improve collision avoidance behavior. The COLREGS' preference towards change of course, rather than speed, for collision avoidance maneuvers, is already reflected in the SBMPC's tuning and the investigation into possible advantages of additional decision points is therefore focused on course modifications. The following paragraphs describe the variants of the multi-step approaches that has been evaluated:

Return-to-Path Prediction In this approach, the cost calculation for each control behavior k includes the search for a point in time where it is safe to return to the planned path. The return time is given by $t_r^* = \min \mathcal{T}_r$, where $\mathcal{T}_r = \{t | t \in \mathcal{T}(t_0), \mathcal{H}_i^k(t_r) = 0 \; \forall \; i\}$. If such a t_r^* exists for the optimal control behavior k^*, a new prediction is made for the ASV's trajectory where the control behavior k^* is applied from time step t_0 to t_r^* and $\chi_m^k = 0$ and $u_m^k = 1$ from t_r^* to T. An example of such a path can be seen in Figure 2. If the return does not incur any cost for collision risk or COLREGS violations, i.e. $\mathcal{H}_i^k(t) = 0 \; \forall \; t > t_r^*$, the return behavior is deemed optimal.

Note that with the current implementation and typical tuning, the maneuvering cost, $f(u_m^k, \chi_m^k)$, is at its minimum when $\chi_m^k = 0$ and $u_m^k = 1$. This means that when an obstacle is passed, and the maneuvering costs are the only concern, the ASV will return to its planned path regardless of earlier predictions. For this reason, maneuvering costs due to the return are not included in the cost of control behavior k^*

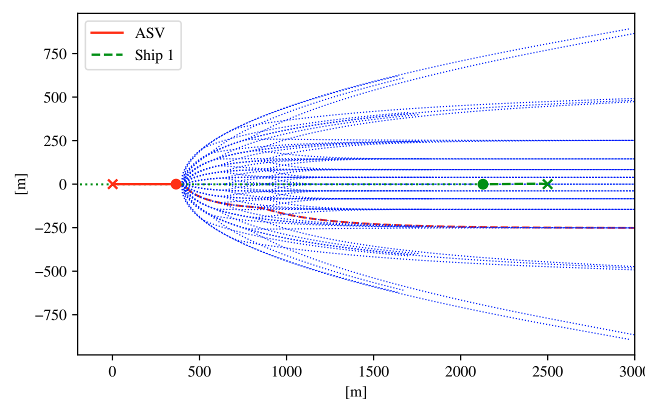


Fig. 3. Predicted paths (····) using SBMPC with additional decision point at time index 100 with $\chi_m^{j_n} \in \{15°, 0°, -15°\}$, along with optimal path (····).

Additional Decision Points This approach gives the possibility of further modifying the course and speed at given points on the prediction horizon. The alternative control behavior modifications are defined by the set J, the elements of which must be coherent with the alternative course modifications already defined for the decision point at t_0 in the set K. With the current implementation they must for instance be divisible by 15, i.e., the increment between the angular values in K for the predicted paths to be viable.

The position of each additional decision point is given by a sample index (s) on the prediction horizon. For a set S of indices containing $N = |S|$ additional decision points, the possible course modifications for each path is given by $\boldsymbol{\chi}_m^{k,\boldsymbol{j}} = [\chi_m^k, \; \chi_m^{j_1}, \; \ldots, \; \chi_m^{j_N}]$, where $\chi_m^{j_n} \in J$, $n = 1 \ldots N$. An example showing predicted paths for $N = 1$ additional decision points, $\chi_m^{j_n} \in \{15°, 0°, -15°\}$, $u_m^k \in [1, \; 0.5, \; 0]$ and $S = \{100\}$ is shown in Figure 3 and Fig. 4.

The increased number of decision points necessitates some changes in the optimization problem and cost function. Notably, the cost must be evaluated with regards to all obstacles for additional course changes to affect the cost.

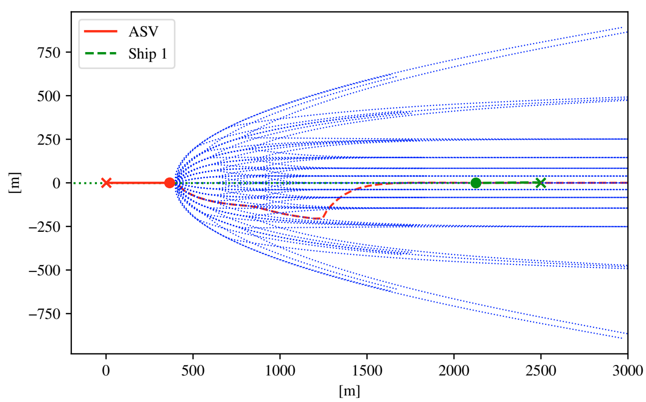


Fig. 4. Predicted paths (····) using SBMPC with additional decision point at time index 100 with $\chi_m^{j_n} \in \{15°, 0°, -15°\}$ and return to path, along with optimal path (····).

This can be achieved by replacing the maximization of obstacle cost with a sum. In addition, the optimization must be extended to include the maneuvering decision at all points, giving the optimization problem

$$(k^*(t_0), \boldsymbol{j}^*(t_0)) = \arg\min_{k,\boldsymbol{j}} \hat{\mathcal{H}}^{k,\boldsymbol{j}}(t_0) \tag{6}$$

with the modified cost function

$$\begin{aligned}\hat{\mathcal{H}}^{k,\boldsymbol{j}}(t_0) = \sum_i \max_{t \in \mathcal{T}(t_0)} \big(&c_i(u_m^k, \boldsymbol{\chi}_m^{k,\boldsymbol{j}}, t) + \mu_i(u_m^k, \boldsymbol{\chi}_m^{k,\boldsymbol{j}}, t) \\ &+ \tau_i(u_m^k, \boldsymbol{\chi}_m^{k,\boldsymbol{j}}, t)\big) + f(u_m^k, \boldsymbol{\chi}_m^{k,\boldsymbol{j}}) \\ &+ e(u_m^k, \boldsymbol{\chi}_m^{k,\boldsymbol{j}}).\end{aligned} \tag{7}$$

Note that to avoid restricting the use of decision points, no maneuvering cost is imposed on the use of these, instead the term e was added. This term gives a penalty on distance from the planned path at the prediction's endpoint, which was done to benefit decision point modifications that brings the vessel back toward it's planned path.

In the case where $\boldsymbol{j}^*$ contains maneuvers, at the next iteration of the multi-step SBMPC a path prediction is also performed with the optimal maneuvers from the previous iteration. If no other control behavior produces a lower cost, this will be considered optimal.

3. SIMULATION SETUP

To examine the value of the extensions described in the previous section, different scenarios were designed to demonstrate their effect. Simulations were then performed for the following variations of the SBMPC method:

(1) Original SBMPC
(2) SBMPC with modified cost function
(3) Multi-step SBMPC (return to path)
(4) Multi-step SBMPC (additional decision points)

For method 4, the number of additional decision points (n_{cp}), the points' time index on the prediction horizon (p_{cp}) and the set of alternative control behaviors (J) must be specified. Simulations were run two sets of possible modifications, $J = \{\pm 15°\}$ and $J = \{\pm 30°\}$, with configurations of number and positions of decision points as shown in table 1. We note that this limited selection is chosen since we have primarily considered head-on and overtaking scenarios, while crossing scenarios would likely benefit from a wider selection of behaviors.

Table 1. Overview of the number (n_{cp}) and position (p_{cp}) of additional change points used in simulations.

n_{cp}	#	p_{cp}				
1	1	50	100	150	200	300
2	1	50	150	100	200	-
	2	100	150	200	300	-
3	1	50	100	150	-	-
	2	100	150	200	-	-
	3	150	200	300	-	-

4. RESULTS

Results from the different modifications are presented in the following sections.

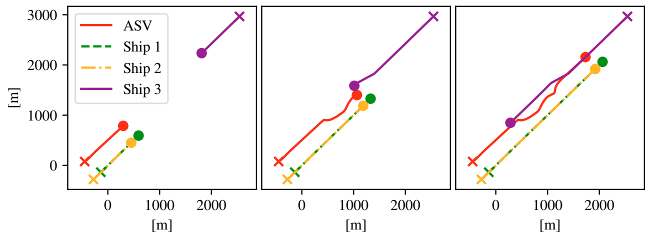
4.1 Cost-function modification

The modified cost function, equation (7), allows all obstacles to be taken into consideration when solving the optimization problem. This is an advantage in multi-vessel encounters such as the one seen in Fig. 5, where the SBMPC is run using the modified cost function and a single decision step at $t = t_0$. In this scenario, the original formulation of the cost function, equation (2), will produce a chattering behavior starting with a starboard maneuver to avoid Ship 3, followed by a port maneuver to avoid Ship 1 or Ship 2, depending on which vessel incurring the highest cost. This behavior continues until the cost of moving closer to either of the obstacles is equally high and an equilibrium is reached. It is difficult to identify a tuning that completely removes this behavior and the modified cost function, which includes the cost with regards to all vessels in the total cost for each control behavior, provides a simple solution that does not affect the behavior in encounters with only two vessels involved.

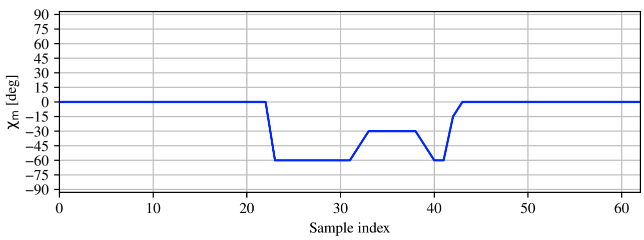
From the offsets shown in Fig. 5b we see four distinct maneuvers. The first is intended to avoid collision with Ship 3 while maintaining a safe distance to Ship 1 and Ship 2. The second and third course modification changes are reactions to Ship 3's evasive maneuver and its subsequent return to the original course. The fourth occurs when Ship 3 is past, and allows the ASV to return to its planned path. While the second and third maneuver may seem excessive, they do demonstrate the SBMPC's ability to adjust according to the behavior of other vessels in situations with limited maneuvering space.

4.2 Return to path

As there is no cost for the return trajectory, this addition does not affect the solution of the optimization problem nor the resulting trajectory of the ASV. However, it does provide a more accurate prediction of the trajectory, see Fig. 6, which must be seen as a clear advantage by anyone charged with monitoring the vessel or using it for decision support.



(a) SBMPC with modified cost function: Trajectory snap-shots. Starting position is marked with (✕).



(b) SBMPC with modified cost function: Course modifications

Fig. 5. Scenario demonstrating the effect of the modified cost function 7 in a multi-vessel encounter.

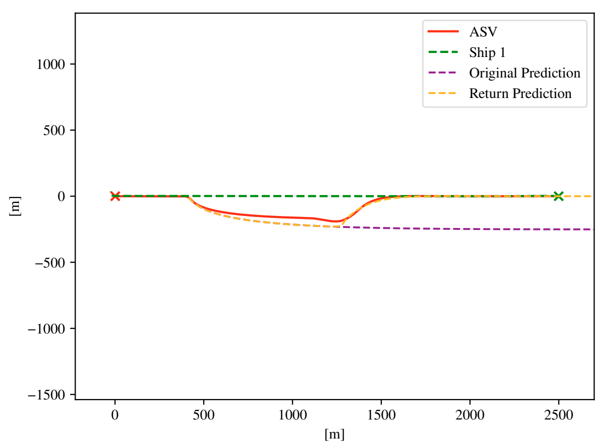
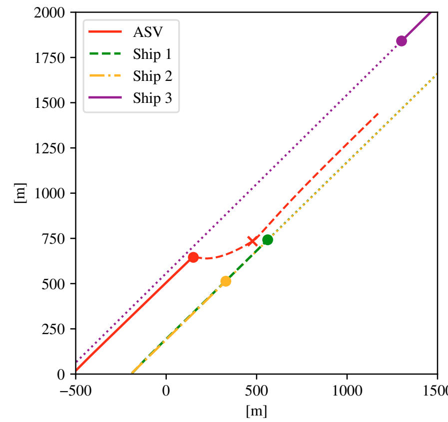


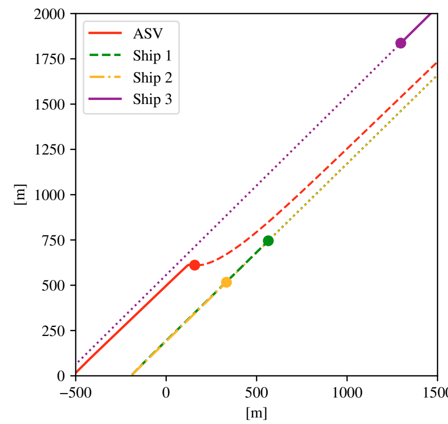
Fig. 6. Difference between predictions with and without return to path prediction in a head-on encounter, compared to the resulting trajectory.

4.3 Additional decision points

While several scenarios were extensively considered and tested, it did prove difficult to identify many realistic situations where the additional decision points would significantly influence the behavior of the ASV. Nevertheless, one scenario in which they were relevant is shown in Fig. 7, where the ASV is in a head on situation with Ship 3 while traveling parallel to two other vessels, Ship 1 and Ship 2. Both for the original and modified SBMPC the situation leads to a starboard course maneuver of 60 degrees, along with a 50 % speed reduction. The simulation employing additional decision points was run with $n_{cp} = 1$ and $p_{cp} = 150$, which allows the ASV to plan to straighten it's course at an earlier point in time as seen in Fig, 7a. We note that the speed reductions leads to further separation of the ships, an effect that is not visualized in in Fig. 7



(a) Snapshot of SBMPC with additional decision point at prediction index 150 (✕).



(b) Snapshot of original SBMPC.

Fig. 7. Scenario demonstrating the effect of additional decision points in a multi-vessel encounter.

5. DISCUSSION

Modifying the cost function to include all obstacles in the cost calculation for each trajectory is an advantage in multi-vessel encounters as it reduces course oscillations that can occur with the original cost function. The trajectory thereby becomes more predictable to other vessels involved in the encounter, an important characteristic to any collision avoidance scheme.

Including the search for a possible return to the planned path does improve the prediction's accuracy, but does not affect the resulting trajectory. However, this is a useful feature with regards to monitoring of the ASV's behavior, as it provides a more complete view of the encounter, which is important when using the method as a tool for decision support. It should be noted that in situations where the course modification is large at the point of return, e.g. 90°, the subsequent course change may appear quite abrupt if the LOS path following strategy is tuned with a short lookahead distance. While clearly fulfilling the COLREGS requirement of being readily observable to other vessels, it should be considered whether a long lookahead distance is desirable or another return strategy is more appropriate.

With regards to the additional decision points it can be argued that the difficulties in creating scenarios where course modifications were triggered, along with the relatively small effect they have on the resulting trajectories can be seen as an indication of robustness in the original SBMPC. It also highlights the problem of how to best place the decision points on the prediction horizon, as this is likely to vary between encounters and will also depend on parameter values used in the SBMPC. It therefore seems unlikely that additional decision points can significantly improve behavior without a more adaptive method for discretizing the candidate control behaviors and a notable increase in runtime. On the other hand, the introduction of multiple decision-points may still be useful in future extensions that consider coordinated collision avoidance control enabled by frequent route exchange and negotiation between vessels Akdag et al. (2022), possibly also including conflict resolution from traffic control centrals.

6. CONCLUSION

A modified version of the SBMPC method implemented in Hagen et al. (2018) has been presented. A simulation study where the original and modified algorithms have been run with the same tuning on different collision avoidance scenarios was performed. The sum of vessel related costs for all vessels in the modified cost function reduces chattering behavior in multi-vessel scenarios, and the prediction of a return path improves the accuracy of the predictions. The results with regards to additional decision points showed a slightly improved behavior in only very few scenarios. This indicates that the existing SBMPC is effective.

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