

Ship Collision Avoidance Using Scenario-Based Model Predictive Control[★]

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Abstract: A set of alternative collision avoidance control behaviors are parameterized by two parameters: Offsets to the guidance course angle commanded to the autopilot, and changes to the propulsion command ranging from nominal speed to full reverse. Using predictions of the trajectories of the obstacles and ship, the compliance with the COLREGS rules and collision hazards associated with the alternative control behaviors are evaluated on a finite prediction horizon. The optimal control behavior is computed in a model predictive control implementation strategy. Uncertainty can be accounted for by increasing safety margins or evaluating multiple scenarios for each control behavior. Simulations illustrate the effectiveness in test cases involving multiple dynamic obstacles and uncertainty associated with sensors and predictions.

Keywords: Autonomous Ships; Collision Avoidance; Trajectory optimization; Hazard; Safety;

1. INTRODUCTION

Rules for ship collision avoidance are given by the Convention on the International Regulations for Preventing Collisions at Sea (COLREGS), (IMO). COLREGS was made for ships operated by a crew, but is to some extent applicable for automatic collision avoidance systems, as decision support systems for the crew or in autonomously operated and unmanned ships, Manley (2008); DNV-GL (2015); Rolls-Royce-Marine (2014); Elkins et al. (2010).

Ship collision avoidance control algorithms, many of them implementing compliance with the main rules of COLREGS, are discussed in Statheros et al. (2008); Tam et al. (2009); Kuwata et al. (2014). They generally do not scale very well to manage a large number of highly dynamic obstacles in dense traffic, and at the same time accurately take into consideration the dynamics of the ship, steering and propulsion system, as well as environmental disturbances such as winds and ocean currents. Some of the methods apply heuristic optimization methods such as evolutionary algorithms or A* search algorithms with a finite planning horizon, e.g. Szlapczynski (2011, 2006); Blaich et al. (2015); Lisowski (2005); Loe (2008). This motivates our investigation on a new approach that employs ideas from optimization-based model predictive control (MPC). MPC is a general and powerful control method that can numerically compute an optimal trajectory on a finite moving horizon based on predictions of obstacles' motion, robustly account for their uncertainty, employ a nonlinear dynamic vehicle model including environmental forces, and formalize risk, hazard, operational constraints

and objectives as a cost function and constraints in an optimization problem. In fact, MPC has been extensively studied for collision avoidance in automotive vehicles, Shim et al. (2012); Gao et al. (2010), aircraft and air traffic control, Bousson (2008), ground robots, Liu et al. (2013) and underwater vehicles, Caldwell et al. (2010).

MPC's main limitations are related to the convergence of the numerical optimization. It is known that complex collision avoidance scenarios may lead to non-convex optimization formulations exhibiting local minimums, and that shortest possible computational latencies are highly desirable for real-time implementation. This makes it challenging to implement an MPC for collision avoidance, and the formulation of models, control trajectory parameterization, discretization, objectives, constraints, numerical algorithms, and representation of uncertainty need to be carefully considered. In order to reap the main benefits of MPC, and mitigate the issues related to local minimums, computational complexity and dependability, one can take a rather simple approach that turns out to be effective and with low complexity of software implementation. More specifically, in the literature on robust MPC the concept of optimization over a finite number of control behaviors is well established, e.g. Bemporad and Morari (1999); Scokaert and Mayne (1998). In its simplest form, it amounts to selecting among a finite number of control behaviors based on a comparison of their cost and feasibility, e.g. Bemporad (1989); Chisci et al. (2001); Kerrigan and Maciejowski (2003), although most approaches also incorporate optimization over some control parameters.

In this paper, we will consider a relatively small finite number of control behaviors, parameterized by offsets to the ship autopilot's course and propulsion command, and merely require evaluation of their performance by simulation. Additional scenarios are created by considering realizations of the uncertain factors such as obstacle trajectories and environmental forces. Hence, we completely avoid numerical optimization and the associated compu-

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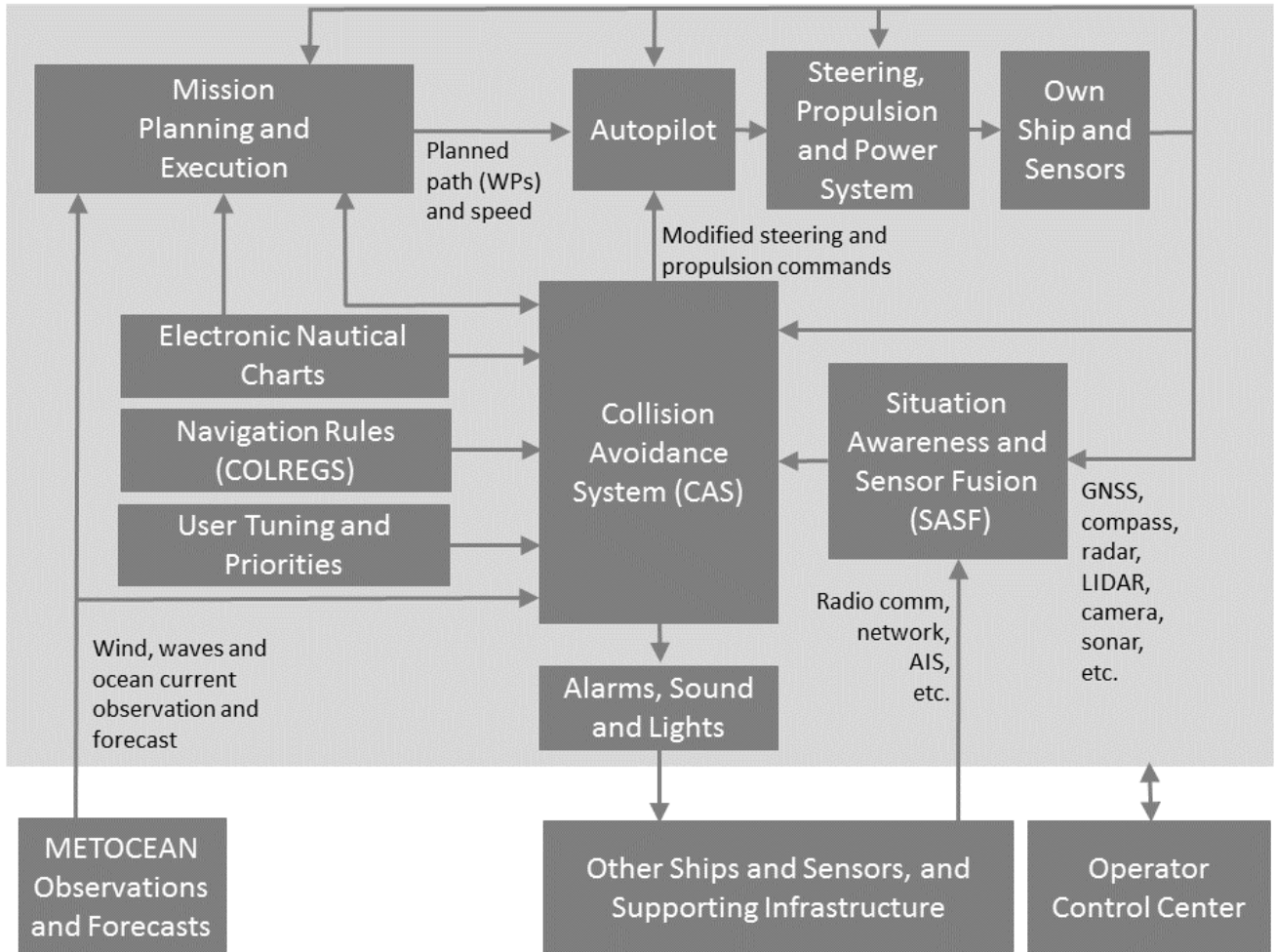


Fig. 1. System architecture.

tation of gradients. This certainly restricts the degrees of freedom available for control, and the selection of the set of alternative control behaviors and scenarios must be carefully considered in order to ensure the required control performance and effectiveness of the collision avoidance system and COLREGS compliance.

2. SYSTEM OVERVIEW

Figure 1 illustrates the proposed system architecture, i.e. the main sub-systems and the information flow.

The ship's autopilot has two basic tasks, which are control of the ship's propulsion (typically constant thrust or power, or tracking of a speed reference) and steering (typically tracking of a course angle or path between way-points). The autopilot interacts with the ship's steering, propulsion and power system in order to execute this task.

Commands to the autopilot, in terms of a nominal speed and nominal path, are given by a high level mission planning and execution system. It plans the mission in order to meet its objective (destination, time of arrival, fuel costs, etc.) while avoiding grounding and collision with mapped hazards that are identified in Electronic Nautical Charts (ENC). This planning often takes into account observations and forecasts of winds, waves and ocean currents provided by METOCEAN services.

The own ship has a set of basic sensors that are used to support navigation, including position and velocity-over-ground provided by GNSS (Global Navigation Satellite Systems) as well as heading provided by a compass. In addition, most ships have a maritime radar system with automatic radar plotting aids (ARPA) in order to detect and track fixed and moving obstacles. Ship's that are designed for autonomous or unmanned operations might also have addition sensors that provide redundancy and potentially enables them to detect and track a wider range of potential obstacles using LIDAR and cameras that can be used to scan the environment of the ship, Elkins et al. (2010); Wolf et al. (2010); Huntsberger et al. (2011). Cameras and microphones may also be needed to receive sound and light signals from other ships and traffic infrastructure.

The use of transponders, radio communication and networking with suitable protocols enable the other ship's to share their position and planned trajectories. Larger ships commonly use AIS (Automatic Identification System) today, and more extensive information sharing is emerging as communication technology is becoming more available and supported by terrestrial or satellite-based communication infrastructure.¹

¹ One may imagine that in the future there will be increased information sharing among vehicles, and by introducing standardized traffic control protocols and collision avoidance algorithms, the ships' collision avoidance systems will be able to quickly negotiate and

The above mentioned information sources all have uncertainties and failure modes that should be accounted for in a robust collision avoidance system. Moreover, the other ships' future trajectories are inherently uncertain as they may be strongly influenced by the other ship's planned paths (which typically must be assumed unknown to own ship), evasive maneuvers, or unexpected maneuvers (e.g. lack of compliance with COLREGS). A Situation Awareness and Sensor Fusion (SASF) module is needed in order to provide a common situation picture with best estimates of the obstacles' positions, velocities and other motion parameters, including estimates of the uncertainty in this information. The SASF system combines information from different sensors and sources (e.g. radar and AIS).

The Collision Avoidance System (CAS) is the decision making algorithm that employs the output from the SASF. Its primary output is modifications to the planned trajectory of the ship, which in our algorithm is parameterized as an alternative propulsion command to the autopilot (e.g. full speed, slow speed, stop or full reverse) and as an offset to the autopilot's course angle command. This parameterization makes it possible to add the CAS to an existing autopilot and mission planner. For example, return towards the nominal path after an evasive maneuver is simply made by setting zero offset to the course angle command. The secondary output of the CAS are light and sound alarms for other ships. The CAS algorithm is the main topic of this paper and will be described in more detail in Section 3.

An important part of the system architecture is the Operator Control Center. It may be located on the ship or onshore, and its purpose is to enable monitoring, fault diagnosis, and operator intervention.

3. COLLISION AVOIDANCE CONTROL

An overview of the proposed CAS control algorithm is shown in Fig. 2. We propose to implement collision avoidance functionality through a finite horizon hazard minimization problem over a finite number of control behaviors in combination with multiple scenarios resulting from uncertainties in predicted obstacle trajectories and environmental forces. The optimization problem is solved in a receding horizon implementation with a re-optimization based on updated information at regular intervals, e.g. every 5 seconds. The hazard associated with the ship trajectory resulting from a given control behavior is evaluated using a ship simulator to make predictions that takes into account the dynamics of the ship, steering and propulsion system, the current position and velocity, the control behavior, as well as wind and ocean current. Robustness is attained by setting an appropriate safety margin and possibly by evaluating additional scenarios resulting from perturbation of the input data to represent uncertainty in obstacle's future trajectories. A cost function measures the predicted grounding and collision hazards, and compliance with the rules of COLREGS, using velocity and line-of-sight vectors to express the COLREGS rules. We emphasize that the proposed optimization is deterministic and guarantees that the global minimum is found after a pre-defined number of cost function evaluation.

3.1 Ship trajectory prediction

In order to predict the ship's motion in response to the different control behaviors as well as wind and ocean reach consensus on collision-free trajectories in a multi-agent system architecture.

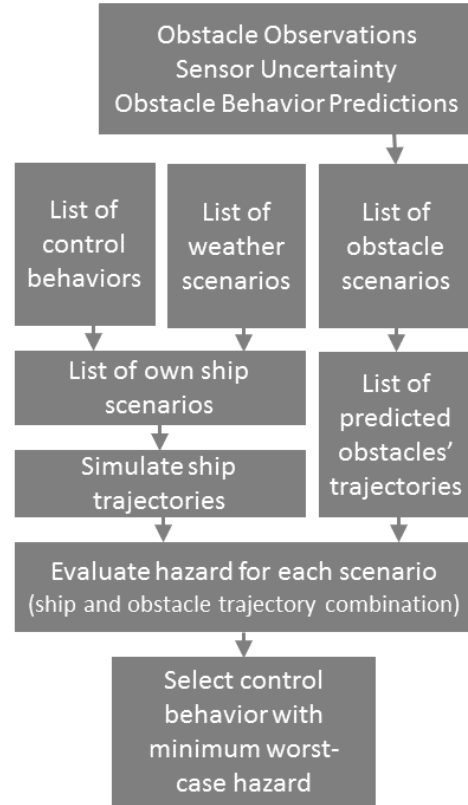


Fig. 2. Summary of the collision avoidance control algorithm.

current disturbance scenarios, we employ the standard 3-degrees of freedom horizontal plane ship dynamics model, neglecting the roll, pitch and heave motions Fossen (2011)

$$\begin{aligned} \dot{\eta} &= R(\psi)v \\ M\dot{v} + C_{RB}(v)v + C_A(v_r)v_r + D(v_r)v_r &= \tau + R(\psi)^T\tau_w \end{aligned} \quad (1)$$

where $\eta = (x, y, \psi)^T$ represents position coordinates and heading in the local earth-fixed frame, where x is North position, y is East position, and ψ is heading angle. Moreover, $v = (v_{surge}, v_{sway}, r)^T$ includes surge and sway velocities and yaw rate decomposed in the body-fixed frame, M is the vessel inertia matrix including added mass, $C_{RB}(\cdot)$ and $C_A(\cdot)$ represent rigid-body and hydrodynamic Coriolis terms, $D(\cdot)$ represent damping,

$$R(\psi) = \begin{pmatrix} \cos \psi & -\sin \psi & 0 \\ \sin \psi & \cos \psi & 0 \\ 0 & 0 & 1 \end{pmatrix} \quad (2)$$

is the rotation matrix from body-fixed to earth-fixed frame, τ represents the commanded thrust and yaw moment, v_c represents the combined effects of the ocean current velocity and wave drift, $v_r = v - v_c$ is the ship's velocity relative to the ocean current, and τ_w is the wind force and moment, both expressed in the earth-fixed frame.

The simulation should account for the dynamics of the propulsion and steering system, and the autopilot functionality. As a typical example, assume the autopilot is executing a LOS guidance control with a given look-ahead distance, Fossen et al. (2003). This leads to a course command χ_{LOS} that guides the ship towards the straight path between the previous and the current selected way-points. The CAS can demand a course angle offset χ_{cao} such that the actual course angle command is $\chi_c = \chi_{LOS} + \chi_{cao}$. A

PI controller for the course steering is then implemented to compute the commanded steering gear (rudder) angle

$$\delta = K_p(\chi_c - \chi) + K_i \int_0^t (\chi_c - \chi) dt \quad (3)$$

where K_p and K_i are gains. As a typical example, the autopilot operates with a constant propulsion command $P \in [-1, 1]$ where 1 is (nominal) forward propulsion, 0 is stop, and -1 is full reverse. A useful property of these control behaviors is that they represent meaningful actions when the control behavior is kept constant on the whole prediction horizon.

3.2 Control behaviors

The following set of alternative control behaviors may be considered as a minimum in a typical implementation:

- Course angle offset χ_{cao} at -90, -75, -60, -45, -30, -15, 0, 15, 30, 45, 60, 75, 90 degrees
- Keep speed (nominal propulsion), slow forward, stop and full reverse propulsion commands.

and all the combinations of the above leading to $13 \cdot 4 = 52$ control behaviors. Assuming the control behavior is kept fixed on the entire prediction horizon, this corresponds to 51 candidate evasive maneuvers in addition to the nominal control behavior with zero course offset, and nominal forward propulsion. Clearly, considering the possibility to change control behavior on the horizon may lead to a ship trajectory with less hazard. However, with one change in control behavior on the horizon this leads to a much larger number of $52^2 = 2704$ scenarios. From a safety performance point of view it is clearly desirable to evaluate as many alternative control behaviors as possible, while from a computational point of view the number of scenarios needs to be kept smaller than the computational capacity, so a trade-off must be made.

3.3 Obstacle trajectory prediction

The collision avoidance problem is linked with considerable uncertainty, as the obstacles' future motions must be predicted. Assuming the SAFS sub-system provides estimates $(\hat{\eta}_i^{lat}, \hat{\eta}_i^{long})$ and $(\hat{v}_i^N, \hat{v}_i^E)$, the simplest short-term predictions of the obstacles' trajectories are perhaps straight line trajectories

$$\bar{\eta}_i^{lat}(t) = \hat{\eta}_i^{lat} + k_{lat} \hat{v}_i^N (t - \tau_i) \quad (4)$$

$$\bar{\eta}_i^{long}(t) = \hat{\eta}_i^{long} + k_{long} \hat{v}_i^E (t - \tau_i) \quad (5)$$

where k_{lat} and k_{long} are constants that convert from meters to degrees in the given area, t is a future point in time, and τ_i is the time of last observation. The straight line prediction approach is also motivated by the observation that some COLREGS rules are stated under implicit steady course situations.

We notice that, in principle, it might be wise to consider the effect of different weather scenarios also when performing predictions of obstacle motion. On the other hand, use of such information is not trivial due to the limited knowledge of obstacle behavior and capabilities

3.4 Scenarios

A finite number of scenarios are generated by combining the possible own ship trajectories generated by

- a finite number of alternative control behaviors;
- a finite number of alternative wind and ocean current scenarios;

with the possible obstacle's trajectories generated by

- uncertainty associated with the observations of the obstacle's positions and velocity;
- uncertainty of the future behaviors of each obstacle.

Whilst the scenarios resulting from the obstacle observation uncertainty can be represented by considering a grid of perturbations to the velocity estimates \hat{v}_i^N and \hat{v}_i^E , and extending the extent of the obstacle to account for position measurement error, it is computationally more efficient to simply increase the safety margins when evaluating the distance between trajectories, see Section 3.5.

Significant uncertainty comes from maneuvers performed by other ships, especially in a multi-obstacles scenarios. As a matter of fact, configurations are admissible such that the application of COLREGS by one of the obstacles might lead to a scenario with a greater hazard compared to the one occurring when all the incoming vessels follow standard straight paths. For this reason, it might be necessary to include in the hazard evaluation scheme some scenarios corresponding to situations like

“ i^{th} obstacle alters its course to STARBOARD”.

Clearly, one major challenge is the uncertainty on the time instant when the action is taken by the vessel. Whilst COLREGS define a set of traffic rules that should lead to expected behaviors, one must also be prepared for the fact that some vessels will not be able, or choose not, to comply with these rules.

3.5 Hazard evaluation criterion

The CAS decides its control behavior by evaluating a finite number of alternative control behaviors in some scenarios using a ship simulator that operates much faster than real time. An important factor in the evaluation of collision hazards is the prediction horizon used to evaluate the result of the simulation scenarios described above. COLREGS demands that early action is taken, so the prediction horizon should be significantly larger than the time needed to make a substantial change of course and speed.

The main information used to evaluate collision hazard at a given future point in time on a predicted ship trajectory generated by a candidate control behavior is illustrated in Figure 3, and detailed as follows:

- The blue curve illustrates the own ship's predicted trajectory, which is a function of the present position, velocity and heading, as well as the control behavior, nominal path given by the way-points, and environmental forces, cf. Section 3.1.
- The red curve illustrates the predicted trajectory of the obstacle with index i , which is a straight line based on the most recent estimate of position and velocity, cf. (4)-(5).
- The blue and red dots denote the predicted position at some future time instant t , while the blue and red vectors illustrate the predicted velocity of own ship and obstacle with index i in scenario k , denoted by the vectors \mathbf{v}_0^k and \mathbf{v}_i respectively.
- The black vector is a unit vector in the LOS direction from own ship to the obstacle with index i in scenario k , denoted \mathbf{L}_i^k .

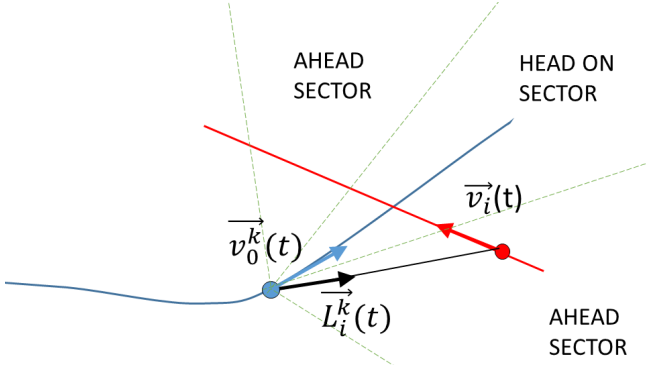


Fig. 3. The main information used for COLREGS compliance and hazard evaluation at a given future time t in scenario k , where the blue dot denotes the predicted position of the own vehicle, and the red dot denotes the predicted position of an obstacle with index i .

Next, some terms relevant for COLREGS are formalized using this terminology and mathematical notation:

- The obstacle with index i is said to be CLOSE to own ship at time t in scenario k if $d_{0,i}^k(t) \leq d_i^{cl}$. Here $d_{0,i}^k(t)$ is the predicted distance between own ship and the obstacle with index i at time t in scenario k , taking into account the shape, size and heading of the obstacle and own ship. Moreover, d_i^{cl} is the largest distance where the COLREGS responsibility to keep out of the way is considered to apply. This distance may depend on the obstacle's and own ship's speed, as well as other factors.
- The obstacle with index i is said to be STARBOARD of own ship at time t in scenario k if the bearing angle of $L_i^k(t)$ is larger than the heading angle of own ship.
- A close obstacle with index i is said to be HEAD-ON at time t in scenario k if the speeds $|v_i(t)|$ and $|v_0^k(t)|$ are not close to zero and

$$\mathbf{v}_0^k(t) \cdot \mathbf{v}_i(t) < -\cos(22.5^\circ) |\mathbf{v}_0^k(t)| |\mathbf{v}_i(t)| \quad (6)$$

$$\mathbf{v}_0^k(t) \cdot \mathbf{L}_i^k(t) > \cos(\phi_{ahead}) |\mathbf{v}_0^k(t)| \quad (7)$$

where ϕ_{ahead} is an angle typically selected as 22.5° .

- A close obstacle with index i is said to be CROSSED at time t in scenario k if

$$\mathbf{v}_0^k(t) \cdot \mathbf{v}_i(t) < \cos(68.5^\circ) |\mathbf{v}_0^k(t)| |\mathbf{v}_i(t)| \quad (8)$$

where 68.5° could be replaced by a more suitable angle depending on the velocity and type of obstacle.

- The ship is said to be OVERTAKEN by the obstacle with index i at time t in scenario k if

$$\mathbf{v}_0^k(t) \cdot \mathbf{v}_i(t) > \cos(68.5^\circ) |\mathbf{v}_0^k(t)| |\mathbf{v}_i(t)| \quad (9)$$

and it has higher speed, and is within a distance d_{ot} of own ship.

Based on this, we define the collision risk factor

$$\mathcal{R}_i^k(t) = \begin{cases} \frac{1}{|t-t_0|^p} \left(\frac{d_i^{safe}}{d_{0,i}^k(t)} \right)^q, & \text{if } d_{0,i}^k(t) \leq d_i^{safe} \\ 0, & \text{otherwise} \end{cases}$$

where t_0 is the current time, and $t > t_0$ is the time of prediction. The distance d_i^{safe} and the exponent $q \geq 1$

must be large enough to comply with COLREGS rule 16, i.e. to take substantial action to keep well clear. Hence, d_i^{safe} may depend on the uncertainty of the prediction of obstacle i 's trajectory. Moreover, d_i^{safe} should account for COLREGS rule 18 by ensuring sufficient safety distance to ships that are fishing, sailing, or appear to not be under command or with restricted ability to maneuver. The exponent $p \geq 1/2$ describes how risk is weighted as a function of the time until the event occurs. The inverse proportionality with the time until occurrence of the event means that avoiding collision hazards that are close in time is being prioritized over those that are more distant. This is important as the short-term predictions of the obstacle trajectories are usually more accurate than long-term predictions, and there is also more time to take action. Typical choices are $q = 4$ and $p = 1$.

A possible enhancement of the collision risk definition is adjusting online the value of the safety distance d_i^{safe} in relationship to the uncertainty margin. For instance, if unpredictable changes in obstacle course and speed are detected based on current and past measurements, it might be wise to enlarge the safety region.

We choose the cost associated with collision with obstacle with index i at time t in scenario k as

$$C_i^k(t) = K_i^{coll} |\mathbf{v}_0^k(t) - \mathbf{v}_i(t)|^2$$

This cost scales with the kinetic energy as given by the relative velocity of the obstacle and own ship, which may be important to consider if ending up in a situation where collision may be unavoidable. The factor $K_i^{coll}(t)$ may depend on several properties such as the type of the obstacle and its size (domain), and own ship's right to stay on or responsibility to keep out of the way.

COLREGS rules 14 demands that in a head-on situation that involves risk for collision, the vessel shall alter course to starboard. COLREGS rule 15 demands that in a crossing situation that involves risk for collision, the vessel which has the other on her own starboard side shall keep out of the way. Let the binary indicator $\mu_i^k \in \{0, 1\}$ denote violation of COLREGS rule 14 or 15 between own ship and the obstacle with index i at time t in scenario k , respectively, where the logic expressions are given by

$$\mu_i^k(t) = \text{RULE14} \mid \text{RULE15}$$

$$\text{RULE14} = \text{CLOSE} \ \& \ \text{STARBOARD} \ \& \ \text{HEAD-ON}$$

$$\text{RULE15} = \text{CLOSE} \ \& \ \text{STARBOARD} \ \& \ \text{CROSSED}$$

$$\& \ \text{NOT OVERTAKEN}$$

This incorporates rule 13 which states that it is the overtaking vessel that shall keep out of the way.

The hazard associated with control behavior j , as predicted based on the available information at time t_0 , is

$$\mathcal{H}^j(t_0) = \max_{k \in S_j} \max_i \max_{t \in D(t_0)} (C_i^k(t) \mathcal{R}_i^k(t) + \kappa_i \mu_i^k(t)) \\ + f(P^k, \chi_{cao}^k) + g(P^k, \chi_{cao}^k)$$

where S_j is the index set of all scenarios associated with control behavior j , t_0 is the current time, and the discrete sample times are given in the set $D(t_0) = \{t_0, t_0 + T_s, \dots, t_0 + T\}$, T_s is the discretization interval, and T is the prediction horizon. The term $g(\cdot)$ represents a grounding penalty that should be defined based on electronic map data and possibly ship sensor data. The term f is included

in order to favor a predictable straight path with constant cruising speed, if possible, as required by COLREGS rule 17:

$$f(P, \delta) = k_P(1 - P) + k_\chi \chi_{cao}^2 + \Delta_P(P - P_{last}) + \Delta_\chi(\chi_{cao} - \chi_{cao,last})$$

where k_P and k_χ are positive weights, and Δ_P and Δ_χ are positive penalty functions that are zero at the origin. The weight k_χ and function Δ_χ are generally asymmetric and gives a higher penalty on course offset commands to port than starboard, in compliance with COLREGS rules 14, 15 and 17. The two last terms in f are included to ensure that the control behavior is not changed unless it gives a significant reduction in the hazard, in order to favor the predictability of the ship's control behavior.

The control behavior with minimal $\mathcal{H}^j(t_0)$ is selected:

$$j^*(t_0) = \arg \min_j \mathcal{H}^j(t_0) \quad (10)$$

This minimization is executed by evaluating all the scenarios and comparing their hazard. The optimal control behavior is commanded to the autopilot that executes the action. The minimization is repeated at regular intervals, e.g. every 5 seconds, in order to account for new sensor information that has been acquired since the previous optimization was executed.

Scalability and computational performance can be managed using parallel processing since each simulation and hazard evaluation can be made independently. Simulations show a tuning can be selected to get acceptable control behaviors for a wide range of cases.

Whilst the selection of tuning parameters is critically important, one need to consider other factors in their tuning, such as technological, economical, ethical and legal aspects beyond COLREGS. This is considered to be outside the scope of this paper.

4. SIMULATION STUDY

The simulation results are illustrated in figures representing snapshots of situations. The following symbols and color codes are applied:

- In the North-East position plots, the black straight line is the path between the two way-points. The black curve is the path of the own ship up to a final time. The small circle denotes d_i^{safe} while the larger circle denotes the d_i^{cl} distance. The green curves denote the paths of the obstacles up to a final time marked by a small green circle. If there are multiple obstacles, their paths are identified by a number.
- The Steering and Propulsion plot shows the propulsion command (dark blue) and rudder angle (black) as a function of time.
- The Hazard plot shows the selected (optimal) hazard $\mathcal{H}^{k^*(t_0)}(t_0)$, with the selected control behavior, as a function of time.
- The Distance plot shows the distance between the own ship and the obstacles. The red line indicates the safety distance, and the blue line indicates the enlarged safety distance to account for increased uncertainty level.

The same tuning parameters of the hazard criterion is used in all cases. In Figure 4 a head-on scenario with a single obstacle is depicted. In compliance with COLREGS, the own

vessel changes its course to starboard in order to reduce the collision risk. Once the collision hazard is over, a second maneuver is then taken to return to the originally planned path. We notice that some chattering in the control appears when the obstacle approaches the boundary of the safety region. This could have been avoided with a more cautious tuning and a smooth definition of $\mathcal{R}_i^k(t)$, but it is interesting to interpret the current results, in particular the tangency of the obstacle path to the boundary of the safety region, see the distance plot at the bottom of Figure 4. This is an indication of the proposed solution being the least conservative according to the given constraints. The same scenario with a second obstacle crossing from starboard is illustrated in Figure 5. As expected, the presence of the second obstacle increases the hazard and hence the selected control behavior commands the ship to make a large turn to the starboard side. Finally in Figure 6 a challenging scenario is presented, assuming a configuration similar to the previous one but where the obstacles instead of moving along a straight path do unpredictably change their course. Due to such uncertainty, the safety distance d^{safe} is increased, and the resulting control behavior is more conservative.

5. CONCLUSIONS

COLREGS compliant collision hazard avoidance based on model predictive control is proposed and studied using simulations. It implements compliance with the main rules of COLREGS and collision hazard avoidance through the evaluation of a performance function along the predicted ship and obstacle trajectories. Environmental disturbances and ship dynamics are incorporated, and uncertainty in obstacle predictions and behaviors can be accounted for.

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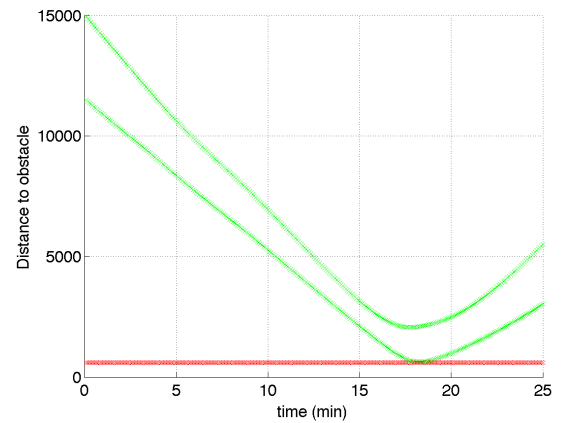
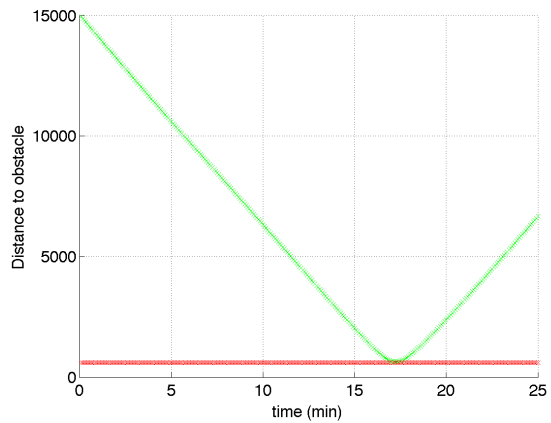
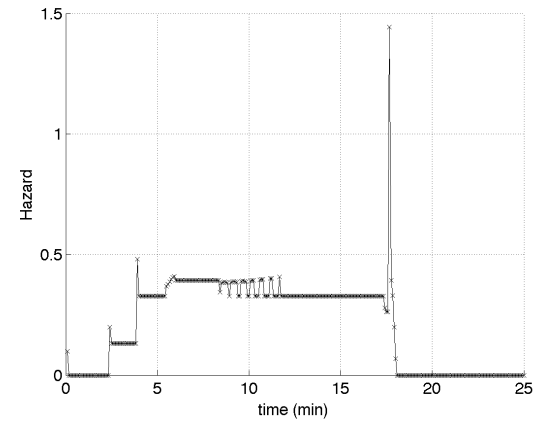
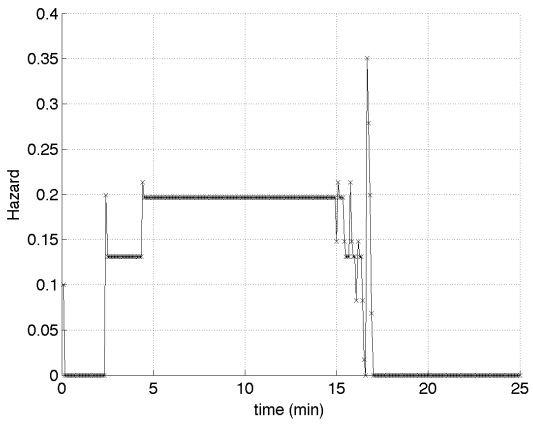
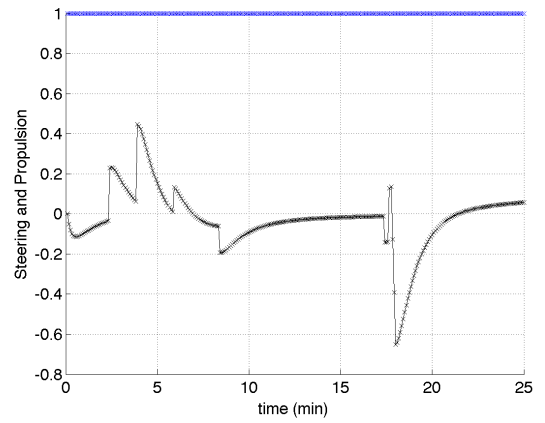
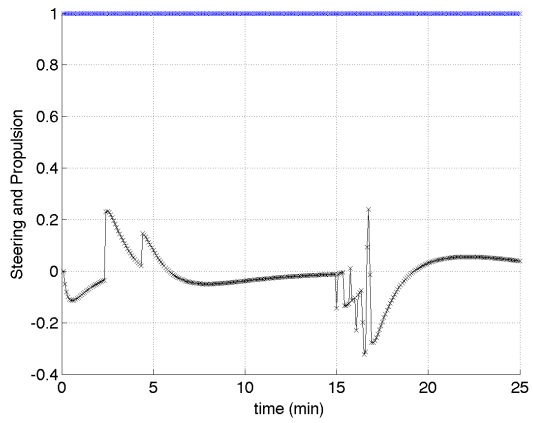
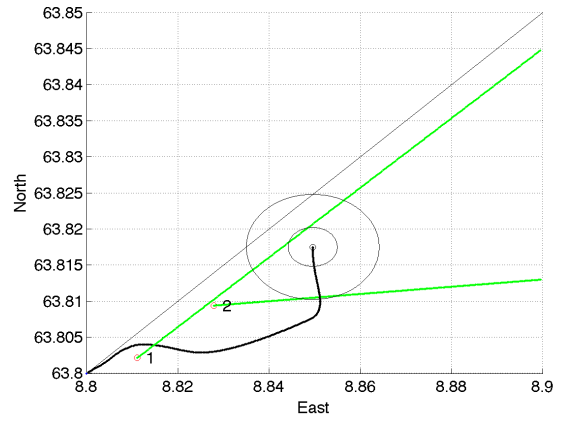
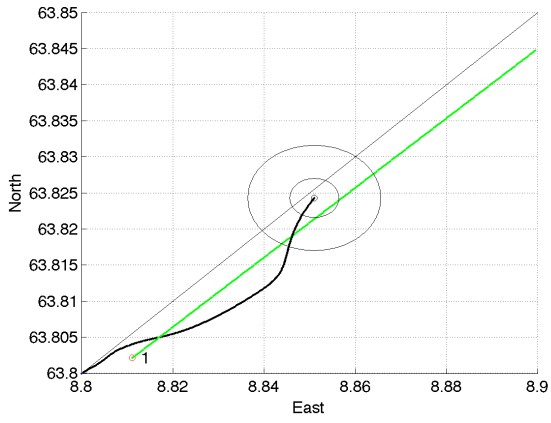


Fig. 4. Single obstacle: head-on scenario

Fig. 5. Multiple obstacles: head-on and crossing scenario

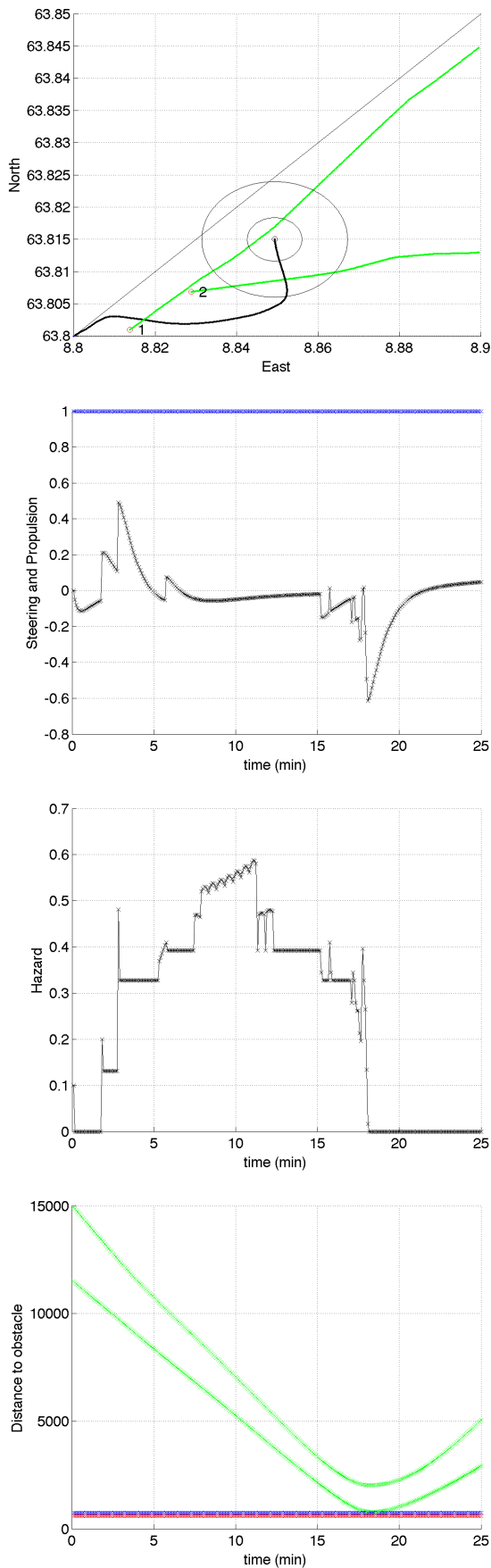


Fig. 6. Multiple obstacles and uncertainty: head-on and crossing scenario

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