Ship Collision Avoidance and COLREGS Compliance using Simulation-Based Control Behavior Selection with Predictive Hazard Assessment

Tor A. Johansen*, Tristan Perez**, Andrea Cristofaro*,***

***Abstract*—This paper describes a concept for a collision avoidance system for ships, based on model predictive control. A finite set of alternative control behaviors are generated by varying 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 simulated predictions of the trajectories of the obstacles and ship, the compliance with COLREGS and collision hazards associated with each of the alternative control behaviors are evaluated on a finite prediction horizon, and the optimal control behavior is selected. Robustness to sensing error, predicted obstacle behavior, and environmental conditions can be ensured by evaluating multiple scenarios for each control behavior. The method is conceptually and computationally simple and yet quite versatile as it can account for the dynamics of the ship, the dynamics of the steering and propulsion system, forces due to wind and ocean current, and any number of obstacles. Simulations show that the method is effective and can manage complex scenarios with multiple dynamic obstacles and uncertainty associated with sensors and predictions.**

***Index Terms*—Autonomous Ships; Collision Avoidance; Trajectory optimization; Hazard; Safety; Control Systems.**

I. Introduction

A. Background

Rules for ship collision avoidance are given by the Convention on the International Regulations for Preventing Collisions at Sea (COLREGS), by the International Maritime Organization (IMO), [1]. Whilst COLREGS were made for ships operated by a crew, their key elements are also applicable for automatic collision avoidance systems, either as decision support systems for the crew or in autonomously operated and unmanned ships [2], [3], [4]. In an autonomous system implementation, COLREGS implicitly impose requirements on the information that must be provided by sensor systems, and the correct actions that should occur in hazardous situations.

Autonomous operation of a ship requires that guidance, navigation and control is performed with high reliability, fault-tolerance, and safety, including real-time perception of the ship's surroundings in order to avoid grounding and collision with other ships, vessels, people, marine mammals or other obstacles that may be encountered. Larger ships are expected to carry an automatic identification system (AIS) transmitting radio signals containing position and other information about the ship, that can be received by other ships and authorities. In order to be able to detect the wide range of potential obstacles, onboard sensors such as radar, LIDAR and camera can be used to scan the environment of the ship, [5], [6], [7].

In this paper, we address the design of the collision avoidance control algorithm, that must decide on the control actions required to ensure compliance with COLREGS and minimize hazard to an acceptable level based on the available sensor information.

B. Literature review and motivation

A wide range of ship collision avoidance control algorithms, many of them implementing compliance with the main rules of COLREGS, are reviewed in [8] and [9]. They generally do not scale very well to manage a large number of highly dynamic obstacles in dense traffic and at the same time can accurately take into consideration the dynamics of the ship, steering and propulsion system, as well as environmental disturbances such as winds and ocean currents. The systematic extension of the existing algorithms to account for such complex situations does not appear to be straightforward. This motivates our investigation on a new approach that employs ideas from optimization-based control and can directly exploit the availability of a simulation model for predictions.

Model Predictive Control (MPC) is a very general and powerful control method that can compute an optimal trajectory based on predictions of obstacles' motion, robustly account for their uncertainty, employ a nonlinear dynamic vehicle model including environmental forces, and formalize risk, hazard and 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 [10], [11], aircraft and air traffic control [12], ground robots [13] and underwater vehicles [14]. Although some elements of optimization and optimal control are used in [15], [16], [17], the authors are not aware of the use of MPC for ship collision avoidance with COLREGS compliance.

MPC can compute optimal trajectories using numerical optimization methods, e.g [18]. Its main challenges are re-

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

**Department of Electrical Engineering and Computer Science, Queensland University of Technology, Brisbane, Australia.

*** Current address: School of Science and Technology (Mathematics Division), University of Camerino, Italy.

Corresponding author: tor.arne.johansen@itk.ntnu.no

lated to the convergence and computational complexity of the numerical optimization. It is widely recognized that complex collision avoidance scenarios may lead to non-convex optimization formulations exhibiting local minimums, and that shortest possible computational latencies is 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, and numerical algorithms need to be carefully considered along with issues such as dependability [19].

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 very effective in terms of high performance and low complexity of software implementation. In the literature on robust MPC the concept of optimization over a finite number of control behaviors is well known, e.g. [20], [21], [22]. 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. [23], [24], [25], although most approaches also incorporates optimization over some control parameters.

C. Contributions

In this paper, we consider MPC with a relatively small finite number of control behaviors, parameterized by offsets to course and propulsion command, and merely require evaluation of their performance by simulation. Hence, we completely avoid numerical optimization and the associated computation of gradients that is inherent in conventional MPC. This certainly restricts the degrees of freedom available for control, and the set of alternative control behaviors must be carefully crafted in order to achieve the required control performance and effectiveness of the collision avoidance system and COLREGS compliance.

We propose to implement collision avoidance functionality through a finite horizon and finite scenario hazard minimization problem over a finite number of control behaviors. The MPC 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 can be enhanced by considering additional scenarios resulting from perturbation of the input data. An MPC cost function considers the constraints and objectives of collision avoidance and compliance with the rules of COLREGS, using velocity and line-of-sight vectors to express the COLREGS rules. The constraints are implemented as penalties in order to ensure that the best possible control behavior can be chosen also when collision with at least one obstacle seems unavoidable.

II. System overview

Figure 1 illustrates the overall concept with its main subsystems and the information flow between them. The nominal input to the ship's Autopilot from the Mission Planner is assumed to be the propulsion or speed-over-ground command, and the desired path given as a sequence of way-points. The Collision Avoidance System (CAS) searches for COLREGS compliant and collision-free trajectories close to the ship's nominal trajectory, given the measured positions and predicted trajectories of obstacles. The CAS outputs a course angle offset and a modified propulsion command that are given to the autopilot. We notice that the CAS needs to consider trajectories (with explicit representation of time) while in the autopilot there is a decoupling of position and time into path guidance (steering) and propulsion control. The speed is normally kept close to a nominal cruise speed, but may be reduced, set to zero, or reversed, upon command from the Collision Avoidance System (CAS). The CAS can also provide alarms such as sound and light signals. In-depth descriptions of the CAS functionality are given in section III. The ship's on-board navigation system provides measurements (usually from a global navigation satellite system (GNSS)) of position and velocity. The accuracy of GNSS position measurements is typically 10 meters or better, which is sufficient for this application. However, the integrity of the GNSS measurements should be analyzed for larger errors such as multi-path, jamming and spoofing. In new systems such as GALILEO this is better handled than in GPS.

In order to support the collision avoidance we assume the following information and capacities are available:

- List of obstacle's positions and velocities, from radar, lidar, AIS, camera or infrared thermal imager, or similar sensors and tracking systems. A detailed description and survey of such systems is beyond the scope of the paper, and we refer to [26], [5], [6], [7] as well as recent results from automotive industry [27], [28].
- Mapped hazards from an electronic map.
- A desired nominal path to the target destination.
- Mathematical model of ship for prediction of future trajectory in order to evaluate the effect of steering and propulsion commands, as well as winds and ocean currents.
- Real-time measurement of the ship's position, velocity, heading and yaw rate.
- Estimates of wind and ocean current forces on the ship.

The proposed architecture implies that the collision avoidance functionality is separated from the mission planning functionality, and the commands from both these systems are executed by the ship's autopilot. This leads to a highly modular architecture that admit the collision avoidance system to be added on top of existing functionality, and such that reliability and safety can be ensured through additional independent and redundancy systems and functions.

A brief overview of the main rules of COLREGS are given in Appendix A.

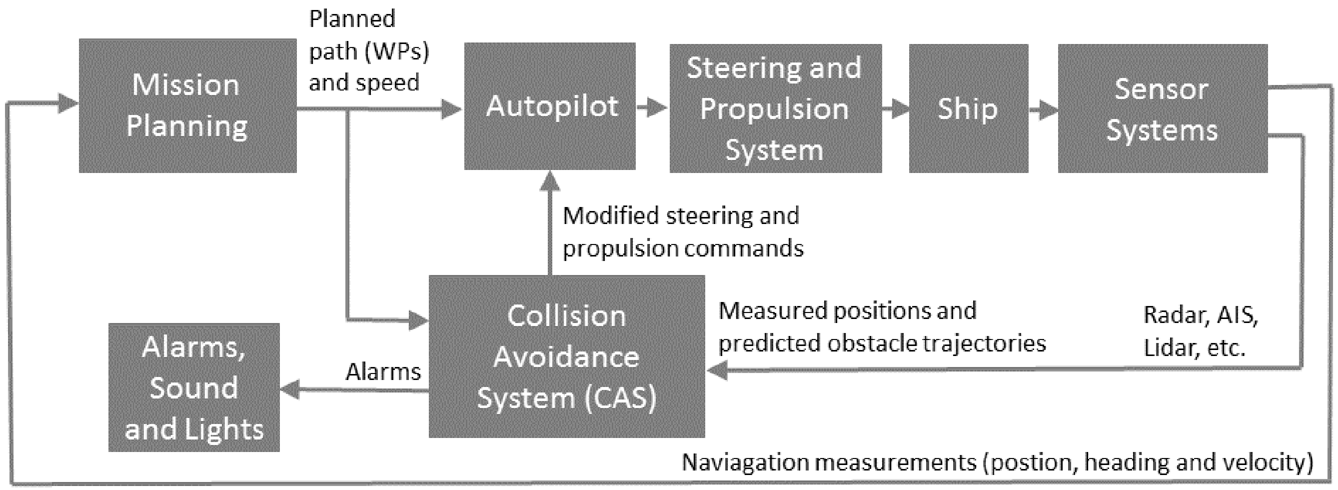

Fig. 1. Block diagram illustrating the information flow between the main modules in the system.

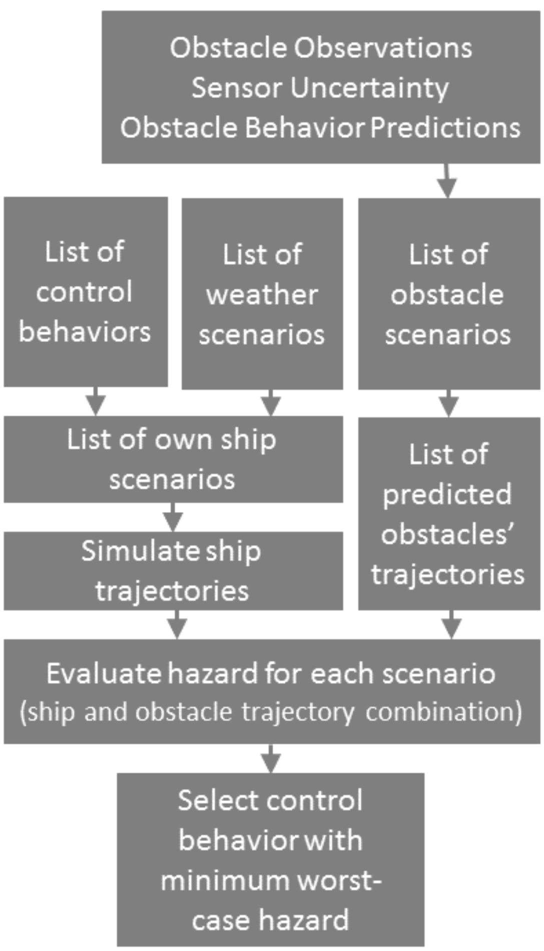

Fig. 2. Summary of the collision avoidnace control algorithm.

III. Collision avoidance system (CAS)

An overview of the proposed CAS control algorithm is given in Fig. 2. The collision avoidance functionality is realized by a finite horizon and finite scenario hazard minimization problem defined over a finite number of control behaviors in combination with multiple scenarios resulting from uncertainties in predicted obstacle trajectories and weather. 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. The proposed optimization is deterministic and guarantees that the global minimum is found after a known finite number of cost function evaluations.

In this section we describe in some detail the main components of the CAS, and their interactions.

A. Obstacle trajectory prediction

The collision avoidance problem is linked with considerable uncertainty, as the obstacles' future motions must be predicted. The simplest short-term predictions of the obstacles' trajectories are perhaps straight line trajectories

$$\overline{\eta}_i^{lat}(t) = \hat{\eta}_i^{lat} + k_{lat}\hat{v}_i^N(t-\tau_i) \tag{1}$$

$$\overline{\eta}_i^{long}(t) = \hat{\eta}_i^{long} + k_{long}\hat{v}_i^E(t-\tau_i) \tag{2}$$

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.

B. Control behaviors and scenarios

Whilst COLREGS define a set of traffic rules that leads 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. Based on this, we make some choices and assumptions.

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. Each scenario is defined by the current state of the ship, the predicted trajectories of the observed obstacles, a control behavior that is either assumed to be fixed on the prediction horizon or by a sequences of control behaviors that are used in different parts of the prediction horizon. The nominal scenario (guidance along the nominal path with no course offset and at nominal speed) is accepted if the hazard is sufficiently low. If not, the least hazardous control behavior is selected among the alternatives that represent a finite number of evasive control behaviors. The predictive simulation should include effects of winds and currents that may have a significant effect on the ship, in particular if the decided control action is to stop. The hazard minimization criterion is based on an evaluation of collision hazard, grounding hazard and COLREGS compliance. The strategy recognizes that there may be conflicting objectives and constraints, such that a sound compromise must be made to determine minimum hazard.

The set of alternative control behaviors should be as extensive as computation time allows, since this will increase the performance of the system. The following set of alternative control behaviors is to be considered as a minimum in a typical implementation:

- Course offset 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 possible 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 planned change in control behavior on the horizon this leads to a much larger number of $52^2 = 2704$ scenarios. From a safety point of view it is clearly desirable to evaluate as many alternative scenarios as possible, while from a computational point of view the number of scenarios needs to be kept smaller than the computational capacity. There is clearly also a trade-off between the number of scenarios and the computational complexity of the simulations in terms of high-fidelity time-discretization, length of prediction horizon, detail of ship model, control update interval and computational latency. Robustness to uncertainty in the prediction of the obstacle's trajectories may also be represented by additional scenarios being perturbations of the obstacles' predicted trajectories, see Section IV-A.

C. Prediction of own ship trajectory

In order to predict the ship's motion in response to the different control behaviors as well as wind and ocean current disturbances, we propose to employ the standard 3-degrees of freedom horizontal plane ship dynamics model, neglecting the roll, pitch and heave motions [29]

$$\begin{aligned} &\dot{\eta} = R(\psi)v + v_c \\ &M\dot{v} + C(v)v + D(v)v = \tau + R(\psi)^T \tau_w \end{aligned} \tag{3}$$

where $\eta = (x, y, \psi)$ represents position and heading in the earth-fixed frame, $v = [v_x, v_y, r]$ includes surge and sway relative velocities and yaw rate decomposed in the body-fixed frame, M is the vessel inertia matrix, $C(\cdot)$ and $D(\cdot)$ model, respectively, Coriolis and damping terms, $R(\psi)$ is the rotation matrix from body-fixed to earth-fixed frame, the input τ represents the commanded thrust and moments, and v_c is the ocean current velocity and τ_w is the wind force, both expressed in the earth-fixed frame.

The simulation should account for the dynamics of the propulsion and steering system, an autopilot that accept a course command to implement the steering control. We assume the autopilot is executing a LOS guidance control with a pre-defined look-ahead distance, [29]. 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 provide a course angle offset χ_{ca} such that the actual course command is $\chi_c = \chi_{LOS} + \chi_{ca}$. A PI controller for the course steering is then implemented to compute the commanded rudder angle

$$\delta = K_p(\chi_c - \chi) + K_i \int_0^t (\chi_c - \chi) dt \tag{4}$$

where K_p and K_i are controller gains. 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 highly useful property of these control behaviors is that they represent meaningful actions when the control behavior is kept constant on the whole prediction horizon. Another useful property is that since the course offset comes in addition to the LOS guidance, then simply setting the course offset to zero will recover the LOS guidance control and the ship will go back to the nominal path without any further planning or guidance.

D. COLREGS compliance

An important factor in the evaluation of collision hazards is the prediction horizon used to evaluate the result of the simulation scenarios described in Section III-B. COLREGS rules 8 and 16 demand 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 COLREGS compliance and 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 current position, velocity

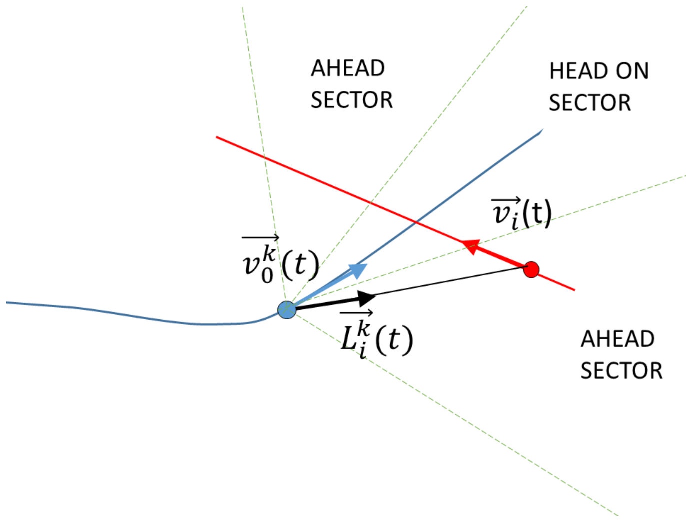

Fig. 3. The main information used for hazard evaluation at a given future time t in scenario k, where the blue dot denotes the predicted position of the own vehicle, and the red dot denotes the predicted position of an obstacle with index i.

and heading, as well as the control behaviors, nominal path given by the way-points, and environmental forces, cf. Section III-B.

- 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. (1)-(2).
- 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 $\vec{v}_0^k$ and $\vec{v}_i$ 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 $\vec{L}_i^k$.
- The obstacle with index i is said to be CLOSE to own ship at time t in scenario k if $d_{0,i}^k(t) \le d_i^{cl}$. Here $d_{0,i}^k(t)$ is the predicted distance between own ship and 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 smallest distance where the COLREGS responsibility for stay away is considered to apply. This distance may depend on the obstacle's and own ship's speed, sensor and prediction uncertainty, as well as other factors.
- The ship is said to be OVERTAKEN by the obstacle with index i at time t in scenario k if

$$\vec{v}_0^k(t) \cdot \vec{v}_i(t) > \cos(68.5^\circ)|\vec{v}_0^k(t)||\vec{v}_i(t)| \tag{5}$$

  and it has higher speed, and is close to own ship.
- The obstacle with index i is said to be STARBOARD of own ship at time t in scenario k if the bearing angle of $\vec{L}_i^k(t)$ is larger than the heading (yaw) angle of own ship.
- The obstacle with index i is said to be HEAD-ON at time t in scenario k if it is close to own ship, and the obstacle speed $|\vec{v}_i(t)|$ is not close to zero and

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

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

  where ϕ_{ahead} is an angle to be selected.
- The obstacle with index i is said to be CROSSED at time t in scenario k if it is close to own ship and

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

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

E. Hazard evaluation criterion

Based on these definitions, we define the collision risk factor

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

where t_0 is the current time, $t > t_0$ is the time of prediction. The distance d_i^{safe} and the exponent $q \ge 1$ must be chosen large enough to comply with COLREGS rule 16, i.e. to take substantial action to keep well clear. This implies that d_i^{safe} may depend on the uncertainty of the prediction of obstacle i's trajectory. Moreover, d_i^{safe} should take into account 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 $p \ge 1/2$ 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 less time to take action. Typical choices are $q = 4$ and $p = 1$.

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

$$\mathcal{C}_i^k(t) = K_i^{coll}|\vec{v}_0^k(t) - \vec{v}_i^k(t)|^2$$

This cost scales with the kinetic energy as given by the squared relative velocity of the obstacle and own ship, which may be important to consider if ending up in a situation with multiple obstacles and 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.

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

$$\begin{aligned} \mu_i^k(t) &= \text{RULE14 or RULE15} \\ \text{RULE14} &= \text{CLOSE \& STARBOARD \& HEAD-ON} \\ \text{RULE15} &= \text{CLOSE \& STARBOARD \& CROSSED} \\ &\quad\ \text{\& NOT OVERTAKEN} \end{aligned}$$

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

The hazard associated with scenario k, as predicted based on the available information at time t_0, is then

$$\mathcal{H}^k(t_0) = \max_i \max_{t \in D(t_0)} \left(\mathcal{C}_i^k(t) \mathcal{R}_i^k(t) + \kappa_i \mu_i^k(t) \right) + f(P^k, \chi_{ca}^k) + g(P^k, \chi_{ca}^k)$$

where t_0 is the current time, and the discrete sample times are given in $D(t_0) = \{t_0, t_0 + T_s, ..., t_0 + T\}$, where T_s is the discretization interval, T is the prediction horizon, and κ_i are tuning parameters. Moreover,

$$\begin{aligned} f(P, \delta) &= k_P(1 - P) + k_\chi \chi_{ca}^2 + \Delta_P(P - P_{last}) \\ &\quad + \Delta_\chi(\chi_{ca} - \chi_{ca,last}) \end{aligned}$$

where Δ_P and Δ_χ are penalty functions that are positive at the origin, and the positive tuning parameters k_P and k_χ influences the priority of keeping nominal speed and course. The parameters k_χ and Δ_χ are generally asymmetric and give a higher penalty on course offset commands to port than starboard, in compliance with COLREGS rules 14, 15 and 17. 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. 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 further enhance the predictability of the ship's control actions.

F. Collision avoidance control decision

The control behavior with minimal $\mathcal{H}^k(t_0)$ is selected among the scenarios $k \in \{1, 2, ..., N\}$ at time t_0:

$$k^*(t_0) = \arg\min_k \mathcal{H}^k(t_0) \tag{9}$$

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 and processed since the previous optimization was executed.

There are several tuning parameters involved. The selection of these parameters is critically important, one need to consider other factors in their tuning, such as technological, economical, ethical and legal aspects beyond COLREGS.

The new method takes advantage of some formulations and ideas in [30], [31], [15] that are embedded into the optimization formulation. 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, in contrast to e.g. evolutionary algorithms where the convergence cannot in general be guaranteed in a finite number of cost function evaluated. Scalability and computational performance can be managed using parallel processing since each simulation and their individual evaluations can be made completely independently.

IV. Robustness enhancements

There are several ways for uncertainties to affect the algorithm and, consequently, to increase the hazard of the selected maneuvers. It may therefore be necessary to enhance the algorithm by letting it be capable of evaluating uncertain cases. The main aspects to be taken care of are uncertainty in the obstacle motion prediction, and uncertainty in environmental disturbances. The robust schemes to be adopted for dealing with such situations will be discussed in this section.

A. Uncertainty on obstacle motion prediction

The prediction of the obstacle motion is a critical point in the algorithm performance, but it is naturally prone to uncertainty. Assuming that the obstacles move along a straight path at a constant speed is sufficient to avoid hazardous maneuvers in many cases, but, in certain scenarios, this might turn out to be a poor and potentially dangerous assumption. A straightforward way to account for uncertainties, and still affordable in terms of computational burden, is to include some additional scenarios, corresponding to the inclusions $|\vec{v}_i(t)| \in \mathcal{V}_i,\ \beta_i \in \mathcal{Z}_i$ where $|\vec{v}_i(t)|, \beta_i$ are respectively the speed and the bearing of the ith obstacle and $\mathcal{V}_i,\ \mathcal{Z}_i$ are discrete sets that include the "straight path" scenario. For instance, given the predicted values v_i^* and β_i^*, a possible and simple choice for the sets $\mathcal{V}_i,\ \mathcal{Z}_i$ is

$$\begin{aligned} \mathcal{V}_i &= \{v_i^* - 1\ m/s,\ v_i^*,\ v_i^* + 1\ m/s\}, \\ \mathcal{Z}_i &= \{\beta_i^* - 3°,\ \beta_i^*,\ \beta_i^* + 3°\}. \end{aligned}$$

It must be pointed out that an additional source of uncertainty comes from maneuvers performed by other ships, especially in a multi-obstacle scenario. 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 worth to enhance the hazard evaluation scheme by considering some additional scenarios, corresponding to situations like

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

Clearly, one major challenge is the uncertainty on the time-step when the action is taken by the vessel.

The algorithm extension can be formally done evaluating, in addition to the standard cases, also the following set of obstacle maneuvers, corresponding to a change of course taken at any time-step in the prediction horizon:

$$\left\{ \begin{array}{l} \text{SCENARIO } \mathcal{N}_{i,k},\ k = 1, ..., N: \\ \beta_i(t_0 + k) = \beta_i(t_0 + k - 1) + \delta\beta \\ \beta_i(t_0 + \ell) = \beta_i(t_0 + k)\ \forall \ell \geq k \end{array} \right\}$$

where $\delta\beta$ is a fixed course offset to STARBOARD. Such parameter may depend on vessel size and type, as well as from the distance between other vessels and/or grounding hazards. The enhanced algorithm will be referred to as *extended* COLREGS-*compliant* framework.

B. Wind and ocean current

Let us finally analyze the case of environmental disturbances. Even though the autopilot is generally capable of compensating for the effect of wind and ocean current while the vehicle is in motion, the presence of disturbances cannot be neutralized when the ship is commanded to stop or to make a sharp turn: drifts or limited turning capabilities are likely to have a significant effect on the ship's trajectory. Thus, when evaluating the best control action, it is worth to take into account the additional input provided by the overall environmental disturbance in order to prevent the selection of scenarios with a potential hazard in the case of perturbed motion, e.g. the natural drift when the vehicle is stopped.

Suppose that an estimate of the environmental disturbances $\tilde{v}_c$ and $\tilde{\tau}_w$ is made available at any admissible position for the ship. Including such terms in the ship motion prediction, some noticeable changes in the evaluation of the control behaviors arise:

- The action $P = 0$ corresponds to the ship predicted response to the estimated disturbances $\tilde{v}_c$ and $\tilde{\tau}_w$ without any control input.
- The action "Course offset" includes the effect of the external inputs $\tilde{v}_c$ and $\tilde{\tau}_w$ on the turning capacity.

V. Simulation study

The purpose of the simulation study is to illustrate the performance of the closed loop control behaviors. The simulations consider a wide range of cases, from single obstacle avoidance to multi-obstacle avoidance, and from predictable obstacle trajectories to complex and random obstacle trajectories that are more difficult to predict. In all simulations, the same parameter settings are used, although the robustness extensions described in Section IV are enables only in some cases in order to illustrate their impact. 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 red circle. If there are multiple obstacles, their paths are identified by a number. The thick red curve denotes the anti-grounding constraint.
- 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 same tuning parameters of the hazard criterion is used in all cases. In general, the tuning is chosen to give a sound tradeoff between the objectives. For example, it is chosen such that course change is prioritized over speed reduction when this does not lead to significantly higher hazard, in compliance

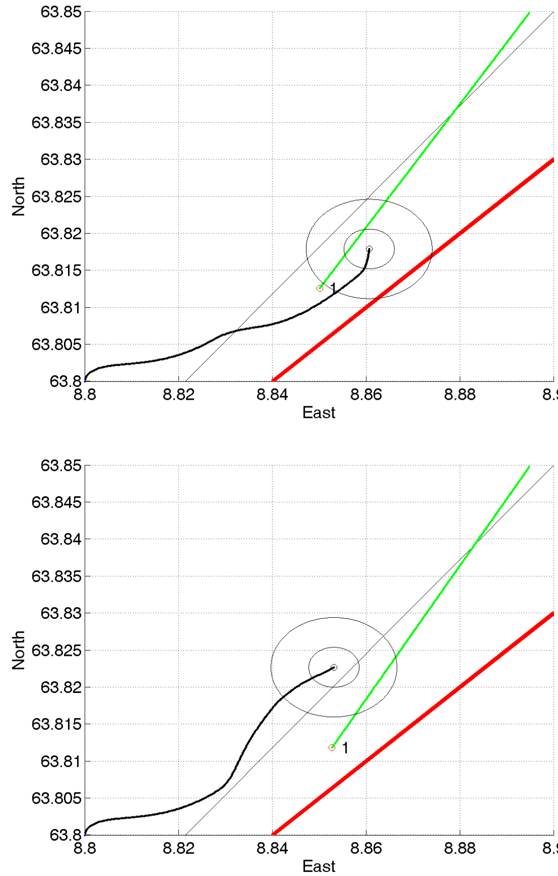

Fig. 4. Single obstacle head-on simulation.

with COLREGS rule 8. The tuning can be easily changed to modify this tradeoff.

A. Single obstacle collision avoidance

Simulations with single obstacle head-on scenarios are given in Figure 4. It can be seen that the ship behavior complies with COLREGS rule 14 and changes course to starboard and passes with the obstacle on her port side when this is safe with respect to collision and grounding. If the distance between the ship and obstacle is so large that COLREGS are considered not to apply, the ship changes course to port and have the obstacle on her starboard side since this path is closer to the nominal path and avoids the grounding hazard. The tuning could easily be changed to slow down or stop instead of change course to port, if desired.

Simulations with single obstacle crossing scenarios are given in Figure 5. The two first cases show an obstacle arriving from the starboard side such that the own ship shall keep away. The ship can either pass ahead or abaft of the obstacle, depending on which low-hazard and COLREGS-compliant trajectory gives smallest deviation from the nominal path. In the two last cases the obstacle arrives from the port side such that the own ship has right to stay on. In these scenarios the obstacle does not respect its responsibility to keep away and the ship makes a maneuver to starboard to avoid collision

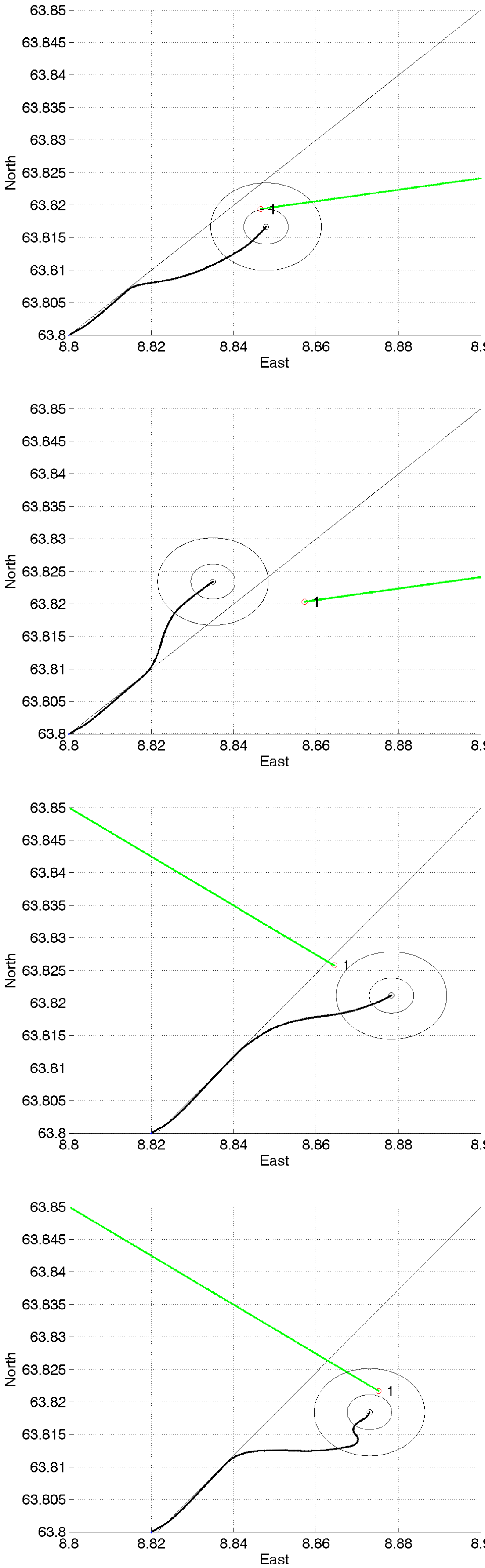

Fig. 5. Single obstacle crossing simulation.

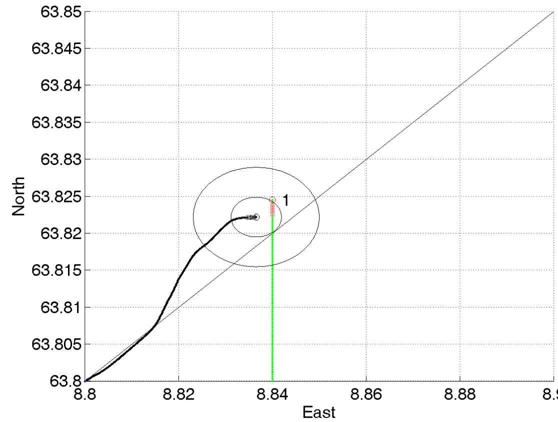

Fig. 6. Single obstacle overtaking simulation.

with some margin and also to avoid a hazardous situation if the obstacle would change course to starboard in compliance with its responsibility to keep clear according to COLREGS.

Figure 6 shows the result of a simulation where the obstacle arrives from abaft and overtakes the own ship. The obstacle makes no attempt to keep away, so the own ship makes a maneuver to avoid collision, and crosses abaft of the obstacle.

In all these cases the own ship continued on nominal propulsion command, as COLREGS compliance and collision avoidance was achieved by change of course only.

B. Collision avoidance with multiple obstacles

In Figure 7 a head-on scenario with several vessels is presented. The optimal control behavior corresponds to a course offset toward starboard side until all the obstacles are passed at a safe distance on own ship's port side. The option of changing course towards port side is not chosen since it will give an additional cost due to the term μ_i^k that measures violation of COLREGS rule 14 in the hazard evaluation criterion.

A scenario with multiple obstacles crossing from starboard side is illustrated in Figure 8. According to COLREGS, the own vessel is requested to stay away. The optimal control behavior corresponds to a course offset toward starboard side until all the obstacles are passed at a safe distance on own ship's port side. Again, the option of changing course towards port side is eventually not chosen since it will give an additional cost due to the term μ_i^k that measures violation of COLREGS rule 15 with obstacles $\#4, 5, 6$ in the hazard evaluation criterion.

Figure 9 illustrates a similar situation with multiple obstacles crossing from starboard side. In this case, the optimal control strategy is make a change in course towards port, since this does not lead to violation of COLREGS rule 15 due to the closest distances being larger than d_i^{cl}. The effect of this control behavior is that own ship passes at a safe distance in front of obstacles $\#1, 4, 3, 6, 2$ (in this order) while at a safe distance abaft of obstacle $\#5$. With a lower penalty on the deviation from nominal propulsion command, the control behavior could be change to make own ship slow down or stop in order to let all obstacles pass in front of her.

Figures 10 illustrates a case when the obstacles arrive from the port side, and the own ship has the right to stay on. Since none of the obstacles make any effort to avoid collision, the own ship makes a course change to avoid it. The course change is to starboard, since a course change to port might increase the hazard if one of the obstacles would change course to starboard (in compliance with COLREGS). The optimal control behavior then leads to own ship passing just in front of obstacles $\#2, 5, 3$ (in this order), and then pass abaft of obstacles $\#1, 4$ and in front of obstacle $\#6$ (assuming they keep course and speed).

C. Robustness enhancement

Figure 11 represents a challenging case which is quite similar to the one presented in Figure 10. While the resulting trajectory is safe, it cannot be said to be very robust. The control behavior selection suffers from the fact that there is no obvious optimal solution and early sub-optimal decisions are taken on the basis on the incomplete information available due to the finite prediction horizon (some obstacles are seen before the others). A more robust control behavior selection is enforced by adding four new scenarios that are generated as perturbations to the predicted obstacle trajectories. The four new scenarios for each obstacle consider ± 1 m/s error in speed, and $\pm 3°$ error in bearing angle. It can be seen in Figure 12 that the resulting control behavior is more cautious and conservative, as the ship stops to wait for the obstacles to pass.

The evaluation of the extended COLREGS-compliant framework described at the end of Section IV-A is depicted in Figure 13. The considered scenario is characterized by the own vessel that is overtaken by a faster vehicle while simultaneously is facing a starboard crossing. In the nominal case, the selected control behavior in the simulation would have been given by a sequence of course offsets to cope with the course offset of the overtaking vessel, this resulting in a very unpredictable path. However, using the extended framework and taking into account in the predictions also the possible application of COLREGS by the other vessels, a smoother path is achieved by temporarily reducing the speed and then applying a single course offset.

D. Wind and ocean current disturbances

Figure 14 illustrates a critical scenario: while the own vessel is overtaking a slower vehicle, two vessels are approaching from port side and other two vessel are approaching from starboard side. Moreover, a side-wind is assumed to blow at 5 m/s in the NW direction. In such overtaking and crossing scenario, the nominal algorithm would have commanded the ship to stop for a sufficiently long amount of time. However, if one adopts the disturbance-sensitive algorithm introduced in Section IV-B, the action $P = 0$ is no longer considered safe due to possible drift, and the selected less-hazard scenario is instead characterized by two subsequent turns on the starboard side.

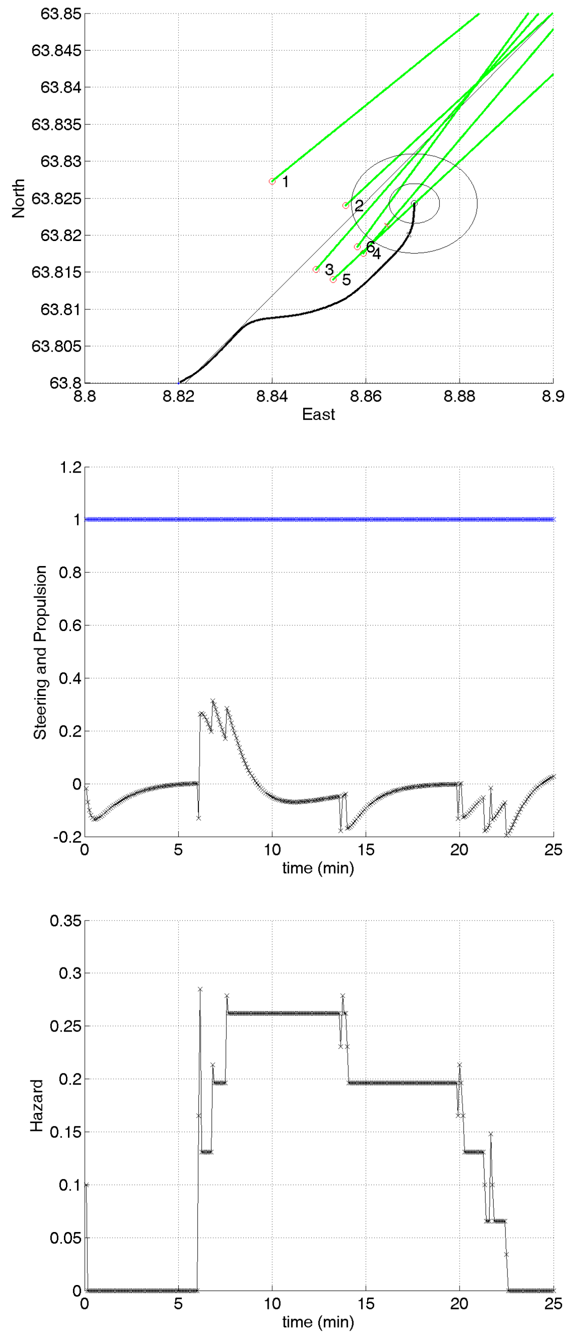

Fig. 7. Multiple obstacles head-on simulation.

E. Obstacles with random motion

Finally, the case of obstacles moving along a random path is proposed in order to emphasize that, even if the obstacle motion predictions are made on the basis of a straight trajectory, the method is still capable to successfully handle the presence of obstacles with unpredictable motion dynamics due to the use of the receding horizon control strategy that re-evaluates the optimal control behavior at regular (5 second) intervals in order to account for new measurements and other information. Figures 15-18 illustrate different scenarios where the relatively low-speed obstacles have random changes in speed and course.

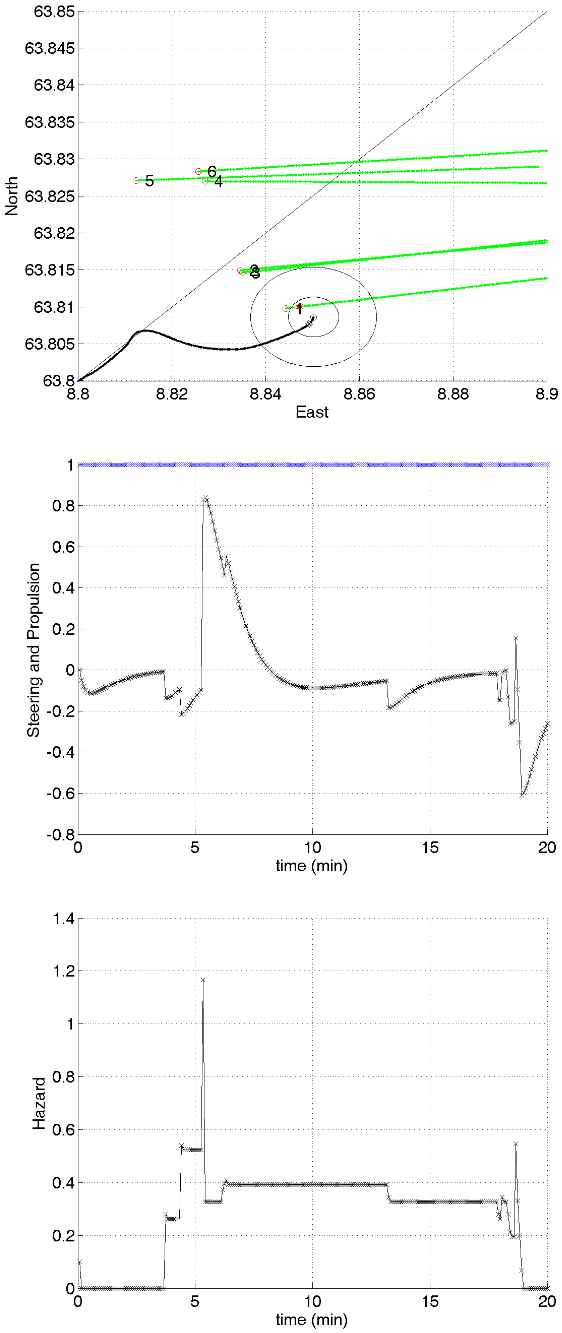

Fig. 8. Multiple obstacles crossing simulation, where own vessel has responsibility to stay away.

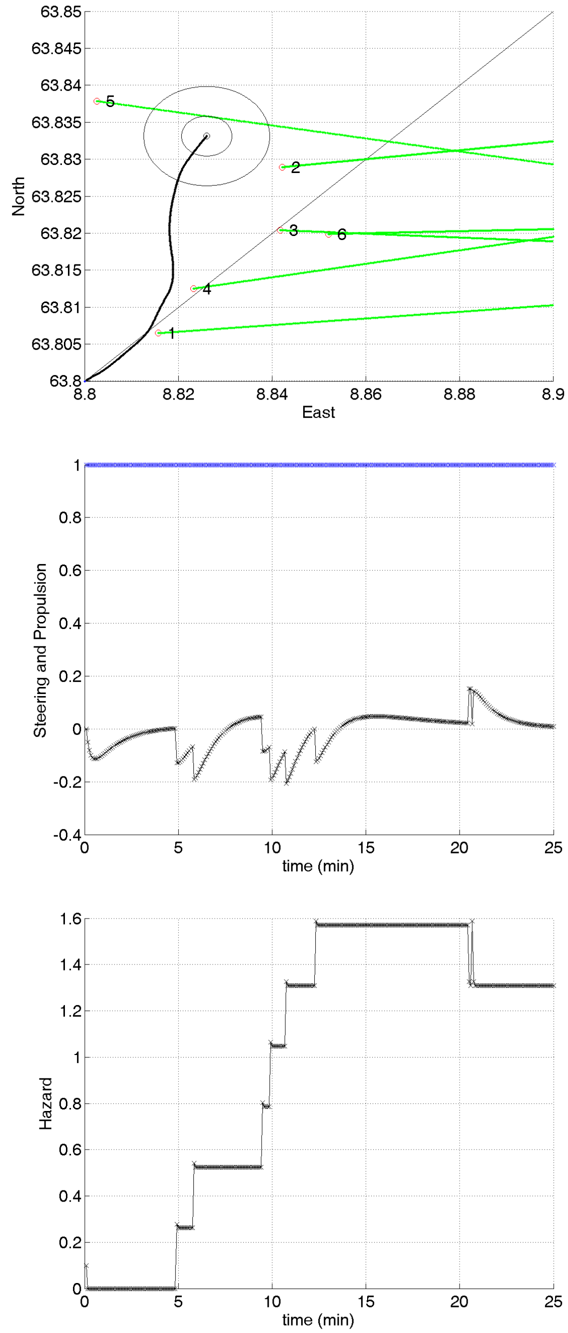

Fig. 9. Multiple obstacles crossing simulation, where own vessel has responsibility to stay away.

In the scenario in Figure 15 own ship changes course to starboard in order to keep away from the obstacles that are moving close to the planned path. The own ship then passes with obstacles $\#2, 3, 4, 5, 6, 7$ on her port side, while obstacles $\#1, 8$ are considered to be sufficiently far away (according to d_c^{cl}) to that they are passed on her starboard side. At the snapshot shown in Figure 15 the own ship has chosen the nominal control behavior (no course offset) and is heading back towards the nominal trajectory according to the LOS guidance law.

In the scenario in Figure 16, the own ship was a $t = 11$ min making a course change to the port since all obstacles are primarily on the starboard side of the nominal path. Then obstacle $\#7$ starts to move towards North-West along a trajectory that would intercept with own ship's planned trajectory. Since own ship would then overtake or cross with obstacle $\#7$ on her starboard side, it is responsible to keep away. It therefore makes a course change to starboard in order to keep away and pass with obstacles $\#7, 8, 6, 5, 2$ at safe distance (according to d_i^{safe} on her port side and with obstacles $\#3, 1, 4$

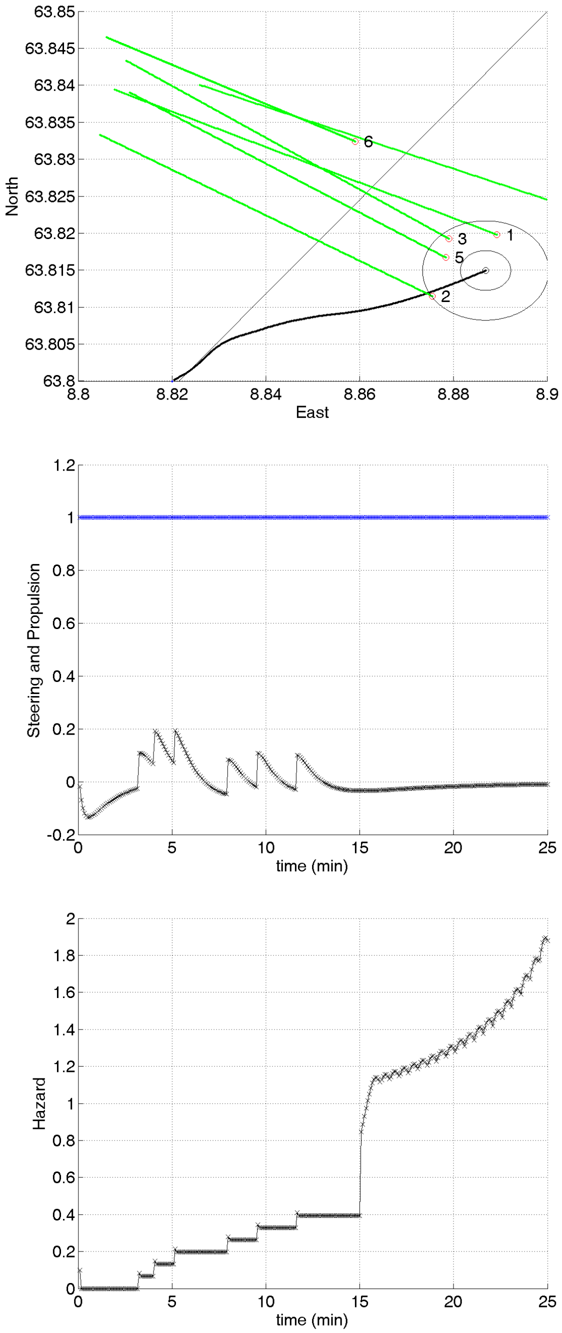

Fig. 10. Multiple obstacles crossing simulation, where own vessel has right to stay on.

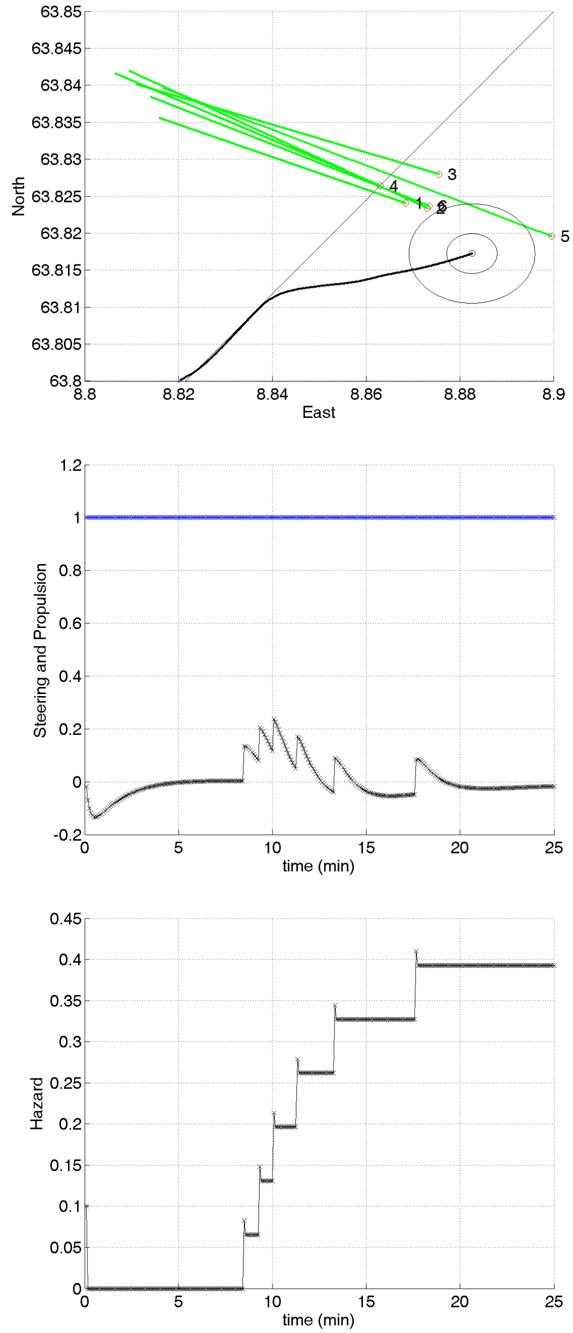

Fig. 11. Multiple obstacles crossing simulation, where own ship has right to stay on.

on her starboard side at at distance where COLREGS is not considered to apply (according to d_i^{cl}).

In the scenario in Figure 17 the own ship changes course to starboard in order to keep away from all obstacles. When obstacle $\#1$ then changes course and speed so as to intercept the trajectory of the own ship, then the own ship has the option of further changing course towards starboard, or stopping. Since the course change would have to be very large and would take own ship far away from the nominal path, the optimal control behavior given by the tuning parameters is to slow down and eventually stop to let obstacle $\#1$ pass in front of her.

In the scenario in Figure 18 the initial control behavior is also to change course towards starboard. When obstacles $\#5, 6, 7$ change their speed and course to intercept the planned trajectory, the own ship chooses to make a sharp turn to port since it allows her to pass all close obstacles at a distance closer than d_i^{cl} on her starboard side. The alternative would be to stop, but this is not chosen due to the tuning that favors to keep nominal cruise speed as long as the path does not

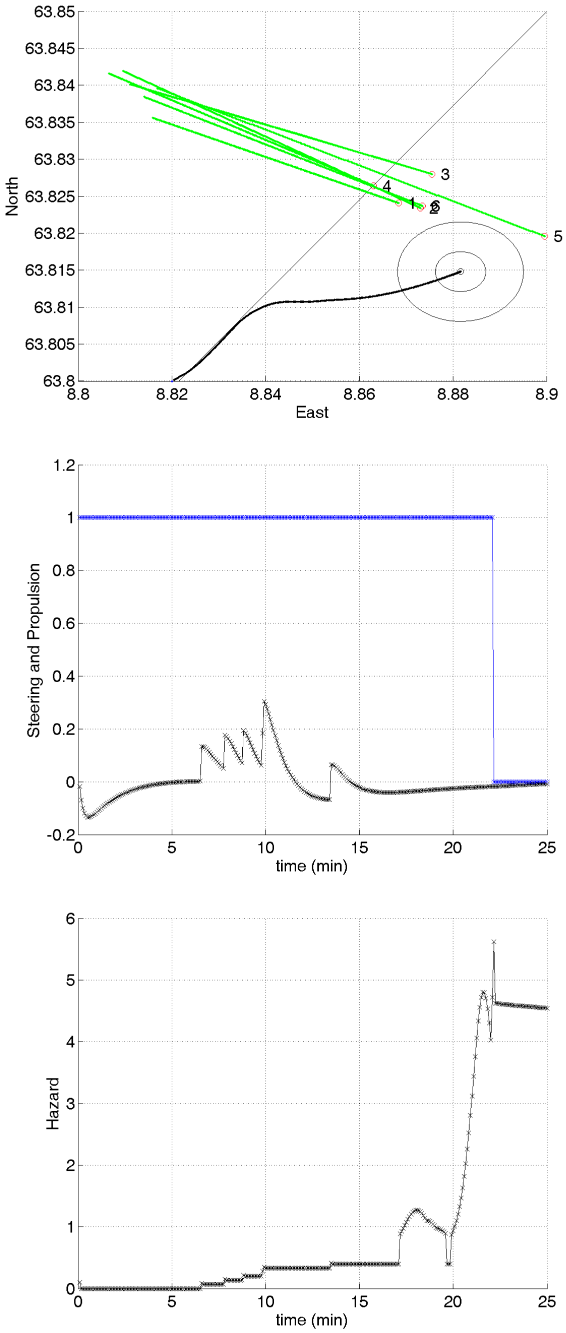

Fig. 12. Multiple obstacles crossing simulation, where own ship has right to stay on, with robustness enhancement.

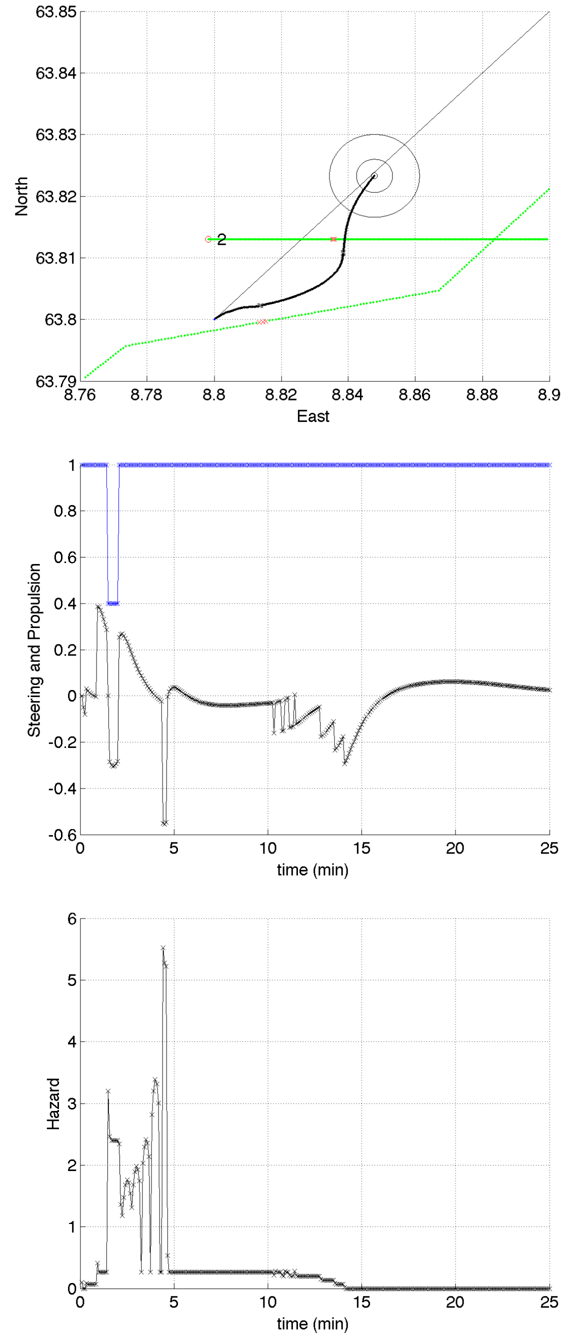

Fig. 13. Multiple obstacles crossing and head-on simulation, extended COLREGS-compliant framework.

deviate too much from the nominal path.

VI. Discussion

For situations with few obstacles, it seems to be sufficient to consider scenarios where there is no change in control behavior on the horizon. When the number of obstacles increase, the CAS would benefit from a more fine-grained set of control behaviors to choose from in order to find a smooth way out rather than making an emergency stop. Also, less conservative safety margins could be possible to achieve by evaluating more scenarios with alternative control behaviors.

There is an extensive set of tuning parameters and functions involved in the CAS. The algorithm can be tuned to exhibit a range of different priorities and behaviors by changing these parameters and functions. Tuning can be time-consuming as the tuning parameters are not completely independent.

The presentation of the method and simulator has focused on the key/main rules of COLREGS, and we have not considered certain special cases such as narrow channels, traffic

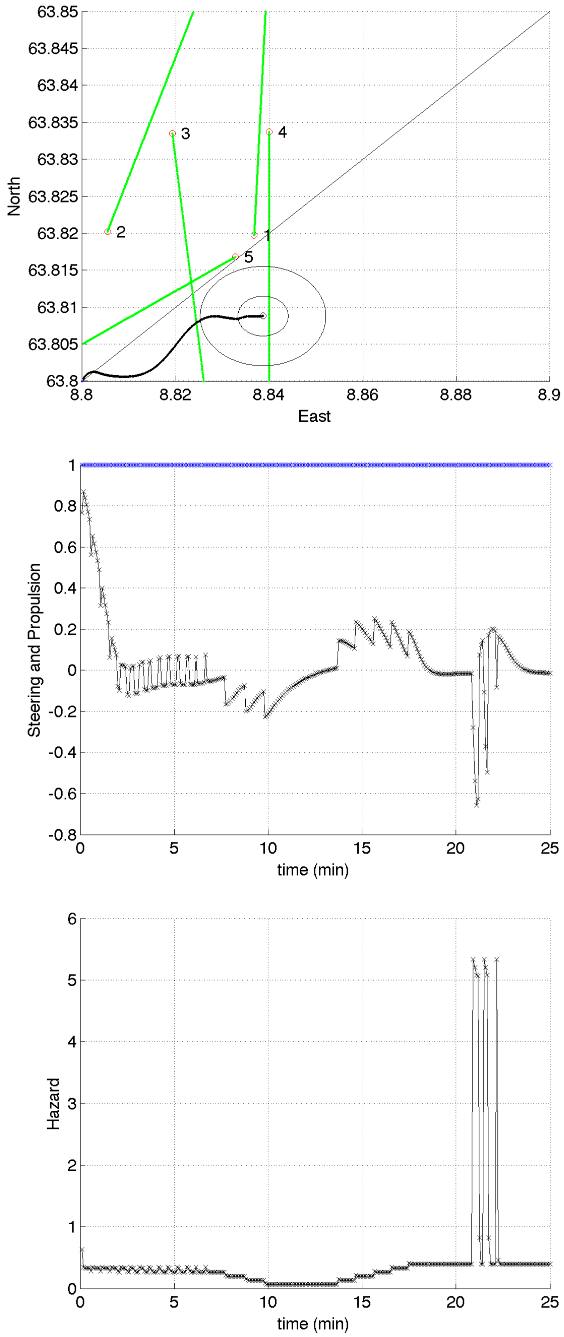

Fig. 14. Multiple obstacles with environmental disturbances evaluation

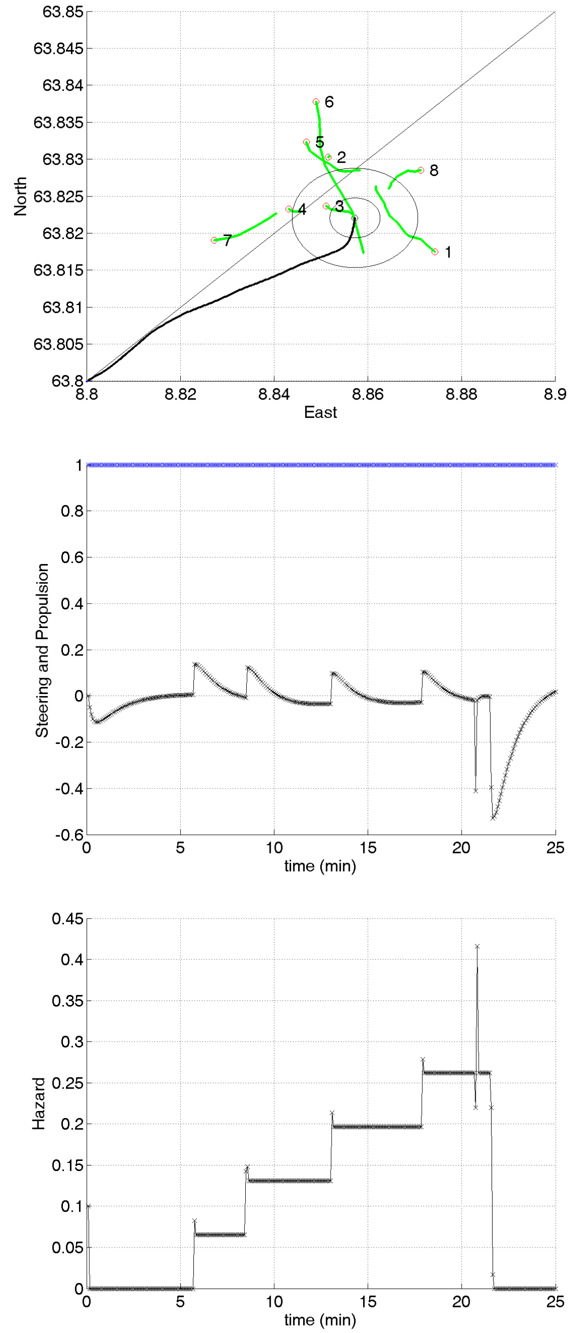

Fig. 15. Multiple obstacles making random changes in course and speed.

separation schemes, nor the modifications needed to operate in extreme weather conditions. We believe these extensions are possible and can be managed by additional logic or dedicated selection of tuning parameters to use under such special conditions.

VII. Conclusions

A collision hazard avoidance method based on simulation and optimization is studied. 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 can be incorporate through the simulation model, and uncertainty in obstacle predictions and behaviors can be accounted for by defining multiple scenarios corresponding to possible realizations of the uncertainty.

Simulations illustrate that the method can be tuned to select acceptable control behaviors for a wide range of cases. The method is conceptually and computationally simple and yet quite versatile as it can account for the dynamics of the ship, its steering and propulsion system, forces due to wind and ocean current, and any number of obstacles. Simulations show

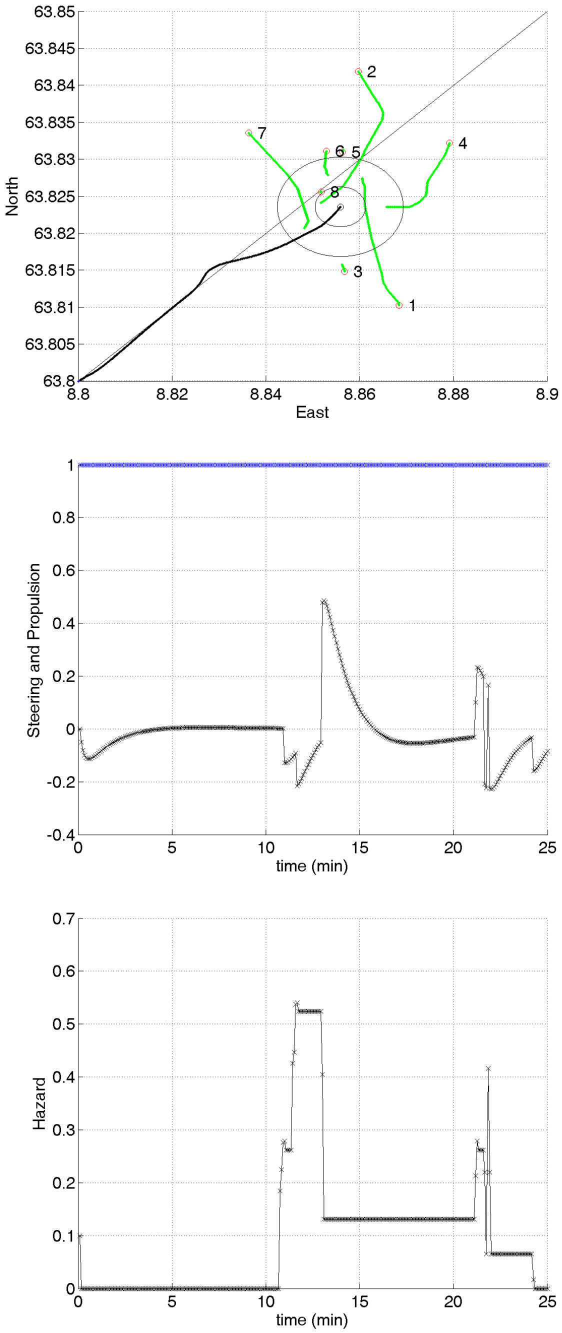

Fig. 16. Multiple obstacles making random changes in course and speed.

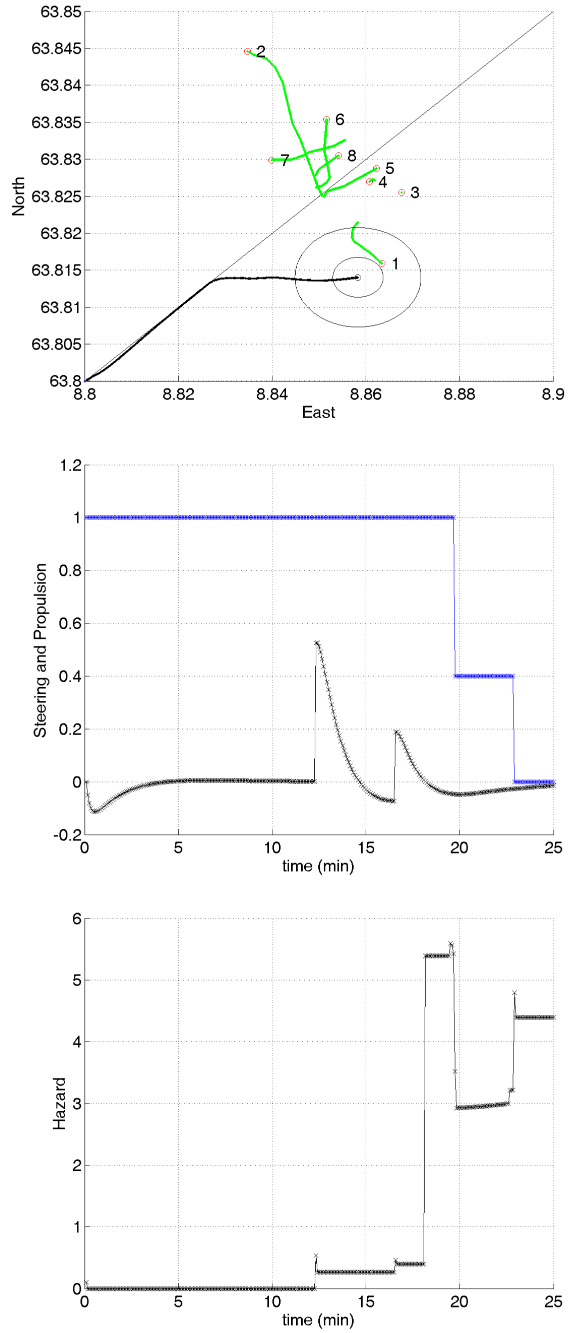

Fig. 17. Multiple obstacles making random changes in course and speed.

that the method is effective and can safely manage complex scenarios with multiple dynamic obstacles and uncertainty associated with sensors and predictions.

The method can be refined further by considering an even richer set of control behaviors and more detailed representations of uncertainty resulting from sensor fusion and obstacle predictions. This would lead to higher computational complexity as the optimization is based on brute force evaluation of all scenarios. Since the algorithm is trivial to implement with parallel processing and the ship dynamics is relatively slow, this is not considered to be an important practical limitation. Systematic methods for selection of tuning parameters and verification (see e.g. [32]) are considered to be important topics of future research.

APPENDIX

This section provides a brief overview of the main technical and operational requirements from COLREGS, [1], relevant for our purpose:

- **Rule 6 - Safe speed**. The following should be considered: Visibility, traffic density, stopping distance and turning

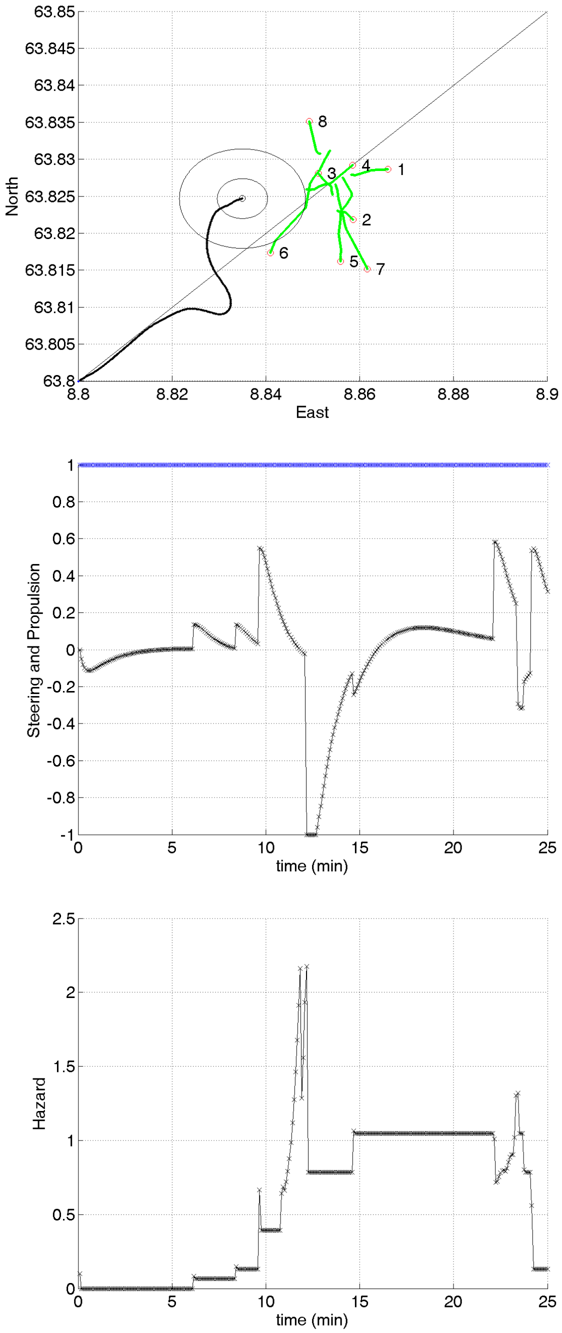

Fig. 18. Multiple obstacles making random changes in course and speed.

ability, wind/waves/current, navigational hazards, draught vs. depth, radar/sensor state.

- **Rule 8 - Actions to avoid collision.** Actions shall be made in ample time. If there is sufficient sea-room, alteration of course alone may be most effective. Safe distance required. Reduce speed, stop or reverse if necessary. Action by the ship is required if there is risk of collision, also when the ship has right-of-way.
- **Rule 13 - Overtaking.** Any vessel overtaking any other shall keep out of the way of the vessel being overtaken. A vessel shall be deemed to be overtaking when coming up with another vessel from a direction more than 22.5 degrees abaft her beam.
- **Rule 14 - Head-on situation.** When two power-driven vessels are meeting on nearly reciprocal courses so as to involve risk for collision, then alter course to starboard so that each pass on the port side of each other.
- **Rule 15 - Crossing situation.** When two power-driven vessels are crossing so as to involve risk of collision, the vessel which has the other on her own starboard side shall keep out of the way.
- **Rule 16 - Actions by give-way vessel.** Take early and substantial action to keep well clear.
- **Rule 17 - Actions by stand-on vessel.** Keep course and speed (be predictable) if possible. If it is necessary to take action, then the ship should try to avoid to alter course to port for a vessel on her own port side.
- **Rule 18 - Responsibilities between vessels.** Except for Rules 9, 10, and 13, a power-driven vessel shall keep out of the way of: a vessel not under command, a vessel restricted in her ability to manoeuvre, a vessel engaged in fishing, and a sailing vessel.
- **Rule 19 - Conduct of vessels in restricted visibility.** Avoid alteration of course to port for a vessel forward of the beam, and avoid alteration of course towards a vessel abeam or abaft the beam, if possible.

In addition, there are requirements for light and sound signals, as well as some rules that apply in special areas denoted as narrow channels and traffic separation schemes.

Acknowledgments

This work was supported by the Research Council of Norway, Statoil, DNV GL and Sintef through the Centers of Excellence funding scheme, Project number 223254 - Centre for Autonomous Marine Operations and Systems (AMOS), and the Research Council of Norway, DNV GL, Kongsberg Maritime and Maritime Robotics through the MAROFF knowledge project 244116 Sensor Fusion and Collision Avoidance for Autonomous Surface Vessels.

References

[1] “COLREGs - convention on the international regulations for preventing collisions at sea, international maritime organization (IMO),” 1972.

[2] J. E. Manley, “Unmanned surface vehicles, 15 years of development,” in *IEEE/MTS Oceans, Quebec City*, 2008.

[3] DNV-GL, “The revolt – a new inspirational ship concept,” 2015, https://www.dnvgl.com/technology-innovation/revolt/index.html.

[4] Rolls-Royce-Marine, “Rolls-royce drone ships challenge $375 billion industry: Freight,” 2014, http://www.bloomberg.com/news/articles/2014-02-25/rolls-royce-drone-ships-challenge-375-billion-industry-freight.

[5] L. Elkins, D. Sellers, and W. R. Monach, “The autonomous maritime navigation (amn) project: Field tests, autonomous and cooperative behaviors, data fusion, sensors and vehicles,” *J. Field Robotics*, vol. 27, pp. 790–818, 2010.

[6] M. T. Wolf, C. Assad, Y. Kuwata, A. Howard, H. Aghazarian, D. Zhu, T. Lu, A. Trebl-Ollennu, and T. Huntsberger, “360-degree visual detection and target tracking on an autonomous surface vehicle,” *J. Field Robotics*, vol. 27, pp. 819–830, 2010.

[7] T. Huntsberger, H. Aghazarian, A. Howard, and D. C. Trotz, “Stereo vision-based navigation for autonomous surface vessels,” *J. Field Robotics*, vol. 28, pp. 3–18, 2011.

[8] T. Statheros, G. Howells, and K. McDonald-Maier, “Autonomous ship collision avoidance navigation concepts, technologies and techniques,” *J. Navigation*, vol. 61, pp. 129–142, 2008.

[9] C. Tam, R. Bucknall, and A. Greig, "Review of collision avoidance and path planning methods for ships in close range encounters," *J. Navigation*, vol. 62, pp. 455–476, 2009.

[10] T. Shim, G. Adireddy, and H. Yuan, "Autonomous vehicle collision avoidance system using path planning and model-predictive-control-based active front steering and wheel torque control," *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering*, vol. 226, no. 6, pp. 767–778, 2012.

[11] Y. Gao, T. Lin, F. Borrelli, E. Tseng, and D. Hrovat, "Predictive control of autonomous ground vehicles with obstacle avoidance on slippery roads," in *ASME Dynamic Systems and Control Conference, Cambridge, Massachusetts, USA*, 2010, pp. 265–272.

[12] K. Bousson, "Model predictive control approach to global air collision avoidance," *Aircraft Engineering and Aerospace Technology*, vol. 80, no. 6, pp. 605–612, 2008.

[13] J. Liu, P. Jayakumar, J. L. Overholt, J. L. Stein, and T. Ersal, "The role of model fidelity in model predictive control based hazard avoidance in unmanned ground vehicles using lidar sensors," in *ASME 2013 Dynamic Systems and Control Conference, Palo Alto, USA*, 2013, pp. V003T46A005; Paper No. DSCC2013–4021.

[14] C. V. Caldwell, D. D. Dunlap, and E. G. Collins, "Motion planning for an autonomous underwater vehicle via sampling based model predictive control," in *IEEE OCEANS*, 2010.

[15] R. Szlapczynski, "Evolutionary sets of safe ship trajectories: A new approach to collision avoidance," *J. Navigation*, vol. 64, pp. 169–181, 2011.

[16] J. Lisowski, "Dynamic games methods in navigation decision support system for safety navigation," in *Proc. European Safety Reliability Conf.*, vol. 2, 2005, pp. 1285–1292.

[17] O. A. G. Loe, "Collision avoidance for unmanned surface vehicles," 2008, master thesis, Department of Engineering Cybernetics, Norwegian University of Science and Technology, Trondheim, Norway.

[18] J. M. Maciejowski, *Predictive control with constraints*. Pearson education, 2002.

[19] T. A. Johansen, "Toward dependable embedded model predictive control," *IEEE Systems Journal*, 2016.

[20] A. Bemporad and M. Morari, "Robust model predictive control: A survey," in *Robustness in identification and control*, ser. Lecture Notes in Control and Information Sciences, A. Garulli and A. Tesi, Eds. Springer London, 1999, vol. 245, pp. 207–226.

[21] P. M. O. Scokaert and D. Q. Mayne, "Min–max feedback model predictive control for constrained linear systems," *IEEE Trans Autom Control*, vol. 43, 1998.

[22] J. Löfberg, "Minimax approaches to robust model predictive control," Ph.D. dissertation, Department of Electrical Engineering, Linköping University, 2003.

[23] A. Bemporad, "Reducing the conservativeness in predictive control of constrained systems with disturbances," in *Proc. IEEE Conf. Decision and Control, Tampa, FL*, 1989, pp. 1384–1391.

[24] L. Chisci, J. A. Rossiter, and G. Zappa, "Systems with persistent state disturbances: Predictive control with restricted contrstraints," *Automatica*, vol. 37, pp. 1019–1028, 2001.

[25] E. C. Kerrigan and J. M. Maciejowski, "On robust optimization and the optimal control of constrained linear systems with bounded state disturbances," in *Proc. European Control Conference, Cambridge, UK*, 2003.

[26] L. Perera, P. Oliveira, and C. Guedes Soares, "Maritime traffic monitoring based on vessel detection, tracking, state estimation, and trajectory prediction," *IEEE Transactions on Intelligent Transportation Systems*, vol. 13, no. 3, pp. 1188–1200, 2012.

[27] A. Mukhtar, L. Xia, and T. B. Tang, "Vehicle detection techniques for collision avoidance systems: A review," *IEEE Trans. Intelligent Transportation Systems*, vol. 16, pp. 2318–2338, 2015.

[28] A. Cherubini, F. Spindler, and F. Chaumette, "Autonomous visual navigation and laser-based moving obstacle avoidance," *IEEE Trans. Intelligent Transportation Systems*, vol. 15, pp. 2101–2110, 2014.

[29] T. I. Fossen, *Handbook of marine craft hydrodynamics and motion control*. Wiley, 2011.

[30] Y. Kuwata, M. T. Wolf, D. Zarzhitsky, and T. L. Huntsberger, "Safe maritime autonomous navigation with COLREGS, using velocity obstacles," *IEEE J. Oceanic Engineering*, vol. 39, pp. 110–119, 2014.

[31] R. Szlapczynski, "Planning emergency maneuvers," *J. Navigation*, vol. 62, pp. 79–91, 2009.

[32] T. Perez, "Ship seakeeping operability, motion control, and autonomy - a bayesian perspective," in *Proc. IFAC Conf. Maneuvering and Control Marine Craft, Lyngby, Denmark*, 2015.

Tor Arne Johansen has received the MSc (1989) and PhD (1994) degrees from the Norwegian University of Science and Technology. He worked at SINTEF Electronics and Cybernetics as a researcher before he was appointed Associated Professor at the Norwegian University of Science and Technology in Trondheim in 1997 and was promoted Professor in 2001. He has published more than 100 articles in international journals as well as numerous conference articles and book chapters in the areas of control, estimation and optimization with applications in the marine, automotive, biomedical and process industries. In 2002 Johansen co-founded the company Marine Cybernetics AS where he was Vice President until 2008. Prof. Johansen is currently a principal researcher within the Center of Excellence on Autonomous Marine Operations and Systems (AMOS) and director of the UAV Laboratory at NTNU.

Tristan Perez completed his Electronics Engineering degree at the National University of Rosario in Argentina in 1999 and his PhD in the area of control engineering at the University of Newcastle, Australia, in 2003. In 2004, he took a Research Fellow position at the University of Wales, United Kingdom, where he worked on fault diagnosis and control of propulsion systems for underwater vehicles – a collaboration with Seaeye Marine (SAAB). In July 2004, Tristan moved to the Norwegian University of Science and Technology (NTNU) where he was a Senior Research Fellow at the CoE for Ships of Ocean Structures (CeSOS). At CeSOS he conducted research in modelling and identification of ship dynamics for motion control. In 2007, he moved back to Australia to the ARC-CoE for Complex Dynamic Systems and Control (CDSC) at the University of Newcastle (UoN). At CDSC, he developed a research program on dynamics and motion control of marine and aerospace vehicles. Within this program, he led 11 projects with 5 industry partners from Australia, New Zealand, Spain, and Norway. In 2010, Tristan was appointed Associate Professor of Mechatronics at the University of Newcastle, where he undertook the re- development of the undergraduate Mechatronics program and developed the laboratory for autonomous systems and robotics. In April 2014, Tristan was appointed Professor of Robotics at the School of Electrical Engineering and Computer Science at The Queensland University of Technology (QUT), where he leads cross-dicsiplinary research in sensing, estimation, and decision making under uncertainty.

Andrea Cristofaro has received the M.Sc. in Mathematics from University of Rome La Sapienza (Italy) in 2005 and the PhD in Information Science and Complex Systems for University of Camerino (Italy) in 2010. He was adjunct associate professor and a post-doc researcher at the Department Engineering Cybernetics, NTNU Trondheim (Norway) in 2014-2016, and is now assistance professor at the University of Camerino. His research interests include: constrained and robust control, optimization methods, nonlinear systems, control allocation, control of partial differential equations.