Cooperative Motion Control of Multiple Autonomous Marine Vehicles:
Collision Avoidance in Dynamic Environments

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Abstract: This paper addresses the problem of cooperative motion control (CMC) of multiple autonomous marine vehicles, taking explicitly into account collision avoidance in dynamic environments. A Collision Avoidance System (CAS) for a CMC architecture is proposed that consists of two subsystems: Collision Prediction and Collision Avoidance. Collision Prediction aims at estimating the most probable trajectory of a given obstacle. To this effect, a bank of Kalman filters are run in parallel, with each filter using a different plausible model for obstacle motion. The most probable model is chosen according to a decision algorithm. Each of the vehicle trajectories is then checked for possible collision with the obstacle. Should the possibility of a collision occur, Collision Avoidance is achieved either by controlling the speed of each vehicle along its assigned path or through path re-planing using harmonic potential fields. Because group coordination must be taken into consideration, collision avoidance is implemented using a decentralized system that is suited for multiple heterogeneous vehicles. The paper summarizes the key concepts and the methodology used to implement a Collision Avoidance System for teams of vehicles. The efficacy of the system is assessed in simulation with dynamic models of a group of marine surface craft using NetMarSys, a Cooperative Motion Control Simulator developed at ISR/IST.

Keywords: Cooperative Motion Control, Collision Avoidance, Collision Prediction, Autonomous Marine Vehicles, Potential field theory, Kalman filtering

1. INTRODUCTION

Often, the execution of multiple vehicle missions requires that the vehicles move in coordination while holding a desired geometrical formation pattern. This problem has been addressed extensively in the literature, both from a theoretical and practical standpoint; see for example Skjetne et al. (2003); Kyrkjebø et al. (2004); Aguiar and Pascoal (2007); Vanni et al. (2008); Ghabcheloo et al. (2009) and the references therein. The problem becomes especially challenging when communication constraints are explicitly taken into account. Another level of complexity arises when the vehicles must react to prevent collisions with stationary or moving obstacles, the location of which is not known a priori. In this case, upon detection of a possible collision, the original formation and/or team speed must change temporarily so as to avoid contact and return to the desired formation pattern/speed afterwards. A representative collision avoidance scenario is shown in Fig.1, where a group of three autonomous surface craft (ASC) performing a cooperative path following mission in formation face a number of static and moving obstacles in their area of operations.

There is a wealth of literature on collision avoidance for autonomous robots moving in environments with static obstacles. See for example Fahimi (2009) and the references therein. The plethora of methods available defies a simple summary. Representative examples include geometrical methods such as the road map and cell decomposition of Bhattacharya P. (2008) or methods that are based on potential field theory, see Yun and Tan (1997). See also Hausler A.J. (2009) where a centralized methodology for multiple vehicle path generation is described that addresses explicitly energy constraints and the goal of reaching specific target locations at the same time. The problem becomes considerably more difficult in the presence of dynamic obstacles. In fact, when moving objects are present in the environment it becomes necessary to predict their behaviour in order for evasive maneuvers to be performed so as to avoid imminent collision situations. Clearly, prediction methods play a key role in any integrated strategy for obstacle detection and avoidance. Representative work along these lines can be found in

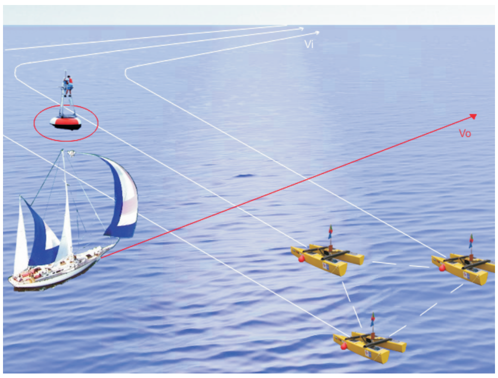

Fig. 1. Collision avoidance: a group of autonomous surface craft on a data-gathering mission at sea.

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Foka A.F. (2002) and Xu Y.W. (2009) that describe the application of partially observable Markov decision process (POMDP) and extended Kalman filters, respectively to the detection of collisions between robotic vehicles and pedestrians.

In this paper, inspired by previous work on collision detection/avoidance and cooperative path following reported in Kim Jin-Ho (1992) and Ghabcheloo et al. (2009), respectively, an integrated solution is offered to the problem of cooperative motion control in the presence of moving obstacles. Our purpose is to contribute to the development of efficient solutions to the abovementioned problem by bringing attention to some of the challenging issues that remain to be solved and to show via simulations, how the integration of existing techniques holds promise for future applications. The solution proposed at this point is supported on an "event-based" architecture, where the vehicles commute from a mission execution state to a collision avoidance state. A collision prediction module acts as the trigger between states. During mission execution, the architecture will naturally yield the following sequence of steps:

(1) Upon detection of an obstacle by one of the vehicles, the latter will track the obstacle and adopt a model for its motion (out of a finite number of possible models). Tracking of the obstacle will continue until it gets out of sensor range.
(2) Based on the model adopted for obstacle motion, and within a given time horizon into the future, the vehicle trajectory will be checked for possible interactions with the obstacle.
(3) In the presence of an imminent collision situation, a collision avoidance mode will be activated according to the type of interaction detected. The ensuing action can be either speed correction or path replanning, based on the type of situation encountered.
(4) The original mission plan is resumed once an obstacle is labeled as harmless; as a consequence, the vehicle goes back to its original mission plan.

The paper is organized as follows. Section 2 gives the reader an overview of the interaction between the Cooperative Control and Obstacle Avoidance Systems. Section 3 details the Target Tracking and Collision Prediction modules, while Section 4 contains the core of the algorithms for Collision Avoidance. Finally, Section 5, includes the results of illustrative simulations. Concluding comments are found in section 6.

2. COOPERATIVE CONTROL AND OBSTACLE AVOIDANCE: AN OVERVIEW

This section describes a Collision Avoidance module and its integration into a cooperative mission control architecture. The rationale for the system can be simply explained with the help of the mission scenario depicted in Fig. 1. In the figure, three autonomous marine vehicles undertake the mission of following an 'L' shaped path, while maintaining a triangular formation among them. Static and moving obstacles intersect the vehicles trajectories, and it is therefore necessary to take preemptive measures to avoid collisions.
The example above displays the two main, possibly competing tasks involved in any cooperative control mission with due account for collision avoidance: i) to execute a specific multiple vehicle maneuver such as cooperative path following or cooperative target tracking; see Aguiar

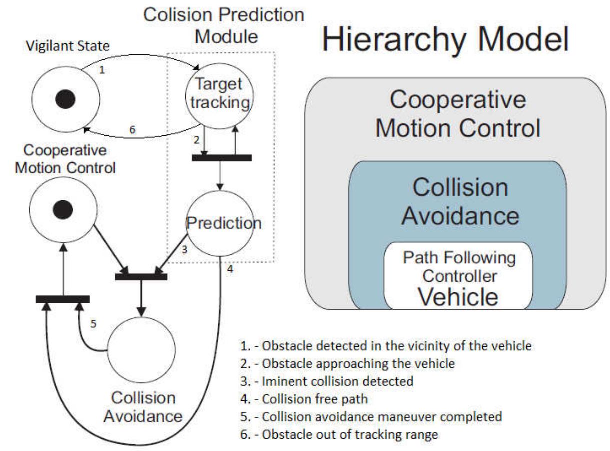

Fig. 2. Petri net representation of an architecture for cooperative control and collision avoidance.

and Pascoal [2007] and ii) to avoid collisions among the vehicles or between the vehicles and static or dynamic obstacles.
Because the execution of both tasks implies obvious trade-offs, it is important to establish a hierarchical relationship between them. In the approach proposed in the paper, it is assumed that for the majority of missions "self preservation" is the priority. Thus, if during mission execution a command for collision avoidance is issued, it will overwrite any command for mission execution control. This behavior can be interpreted as the transition between two states, a mission state and a collision avoidance state.
The abovementioned hierarchical organization is clarified in Fig. 4, as embodied in a Petri net. In the presence of an obstacle at sensing range, the Target Tracking stage is launched and kept alive until the obstacle is out of range. Target tracking provides for a model from which to derive the probable trajectory of the obstacle. Collision Prediction can then determine if a collision is imminent, and trigger the transaction to the Collision Avoidance state. The Collision avoidance module then takes the necessary measures to ensure that collision is avoided. As explained later, this can be done by changing, for each of the vehicles, the path or the velocity profile planned for the mission. Once the maneuver is completed, and if no more imminent collisions are detected, the mission execution state can resume. In the sections that follow we describe briefly each of the relevant modules involved in Collision Prediction / Avoidance.

3. TARGET TRACKING AND COLLISION PREDICTION

The ability to successfully avoid collision with an obstacle is closely related to how far in advance a vehicle can become "aware of it", even more so when the obstacle is moving. Being able to predict a collision ahead of time, will not only give the vehicle time to react to dynamic obstacles, but also the ability to do so in a safe and smooth manner. This requires putting together the Target Tracking and Collision Prediction modules that are described next.

Target Tracking

Target tracking is activated once an obstacle is at sensor range (e.g. radar at the surface or a sonar underwater). It is assumed the position of the obstacle can be determined at every interrogation time step and that the measurement error is adequately described (at least for design purposes) by a stochastic Gaussian process with zero mean. During the time window over which the trajectory is to be predicted, it is assumed that the obstacle has bounded linear and angular velocities denoted by v and ω, respectively and that its behavior is described by the kinematic model

$$\begin{cases} \dot{x} = v\cos(\theta) \\ \dot{y} = v\sin(\theta) \\ \dot{\theta} = \omega \end{cases} \tag{1}$$

where $(x, y)^T$ is the position of the center of mass of the obstacle in 2D and θ denotes path angle. To estimate v and ω and thus predict the trajectory followed by the obstacle, an Interactive Multiple Model Kalman filter (IMM-KF) is used. The IMM-KF is a nonlinear filter that is composed by a bank of Kalman filters running in parallel, each one using a different model for target motion. The output of the IMM-KF is the state estimate given by a weighted sum of the state estimations produced by each Kalman filter. The weights are on-line adjusted according to the priori probabilities of each KF. Further details on the IMM-KF can be found in the book by Bar-Shalom Y. and X.R. (2002). For the implementation of the IMM-KF in the collision prediction module the solution developed in M. Bayat and Aguiar (2009) was applied. In this set-up, each Kalman filter j is designed according to the following discrete process model with a constant sampling time t_s (the speed v has been added as an extra state variable):

$$\begin{cases} x_{k+1}^j = x_k^j + t_s v_k^j \cos\theta_k^j \\ y_{k+1}^j = y_k^j + t_s v_k^j \sin\theta_k^j \\ \theta_{k+1}^j = \theta_k^j + t_s\omega^j + \eta_{\theta k}^j \\ v_{k+1}^j = v_k^j + \eta_{vk}^j \end{cases} \tag{2}$$

where k is a discrete time index, v_k^j is linear speed, and ω^j is angular speed, which takes a finite set of values between w_{min} and w_{max}, including 0 (straight line motion). Notice that ω^j is constant for each model j. In (2), $\eta_{\theta k}^j$ and η_{vk}^j denote zero mean stochastic Gaussian processes with appropriate covariances. At this point it is convenient to stress that the option for an IMM-KF instead of the standard EKF is due to the fact that the IMM-KF exhibits superior performance (Bar-Shalom Y. and X.R., 2002). This fact is particular important for this type of marine scenarios where the dynamic obstacles are typically marine vehicles that can rapidly change their course.

Collision Prediction

Once a set of state variables x, y, v, and θ of the obstacle kinematic model have been determined at some point via the target tracking system, it then becomes possible to predict its motion over a time window into the future by resorting to model (1). Furthemore, because the vehicle is performing a mission along a pre-defined path, it can be determined if a collision between the vehicle and the object is likely to occur.

It is important to stress that even though a larger time window could in principle help predict collisions further in advance, it may also add increasing uncertainty to the estimated position of the obstacle position. For these reasons, it is important to use for each complete prediction cycle a Time Varying Dynamic Window (TVDW), the length of with reflects prior knowledge on vehicle cruising speed, expected obstacle linear and angular speeds, etc. In this work, the computation of the TVDW length at time t_0, denoted W^{t_0}, takes into account the time required for a vehicle to come to a complete halt when traveling a certain speed, as follows:

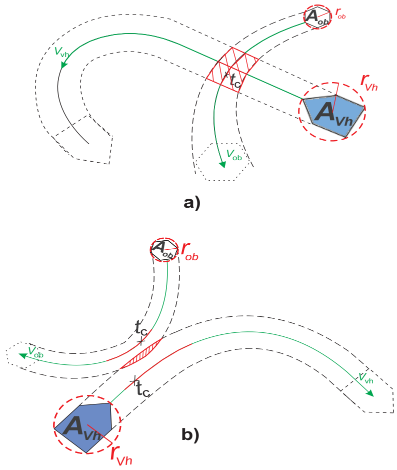

Fig. 3. Collision scenarios in an environment with dynamic obstacles

$$W^{t_0} = [t_0, t_0 + \delta], \quad \delta = \frac{v_0}{a} + \zeta,$$

where v_0 is the velocity of the vehicle at time instant t_0, a is the maximal breakage deceleration of the vehicle undergoing translational motion, and ζ is a desired safety margin. The methodology adopted for collision prediction between a vehicle and a moving obstacle is illustrated in Fig. 3, where two different scenarios are shown. Let A_{vh}^0 and A_{ob}^0 denote polygonial regions that bound the actual areas occupied by the vehicle and the obstacle, respectively at time t_0. The evolution of these regions in 2D space can be described formally as

$$A_{vh}^t = \Phi_v(x_v(.), y_v(.), A_{vh}^0), \quad \forall t \in W^{t_0}$$
$$A_{ob}^t = \Phi_o(x_o(.), y_o(.), A_{ob}^0), \quad \forall t \in W^{t_0}$$

where $\Phi_v(.)$ denotes a transition operator from region A_{vh}^0 to region A_{vh}^t at time t, based on the evolution of the position $x_v(\tau), y_v(\tau)$ of the vehicle for $\tau \in [t_0, t]$. Similar conditions and notation apply to the obstacle. Formally, there is potential for a collision to occur at time $t_c \in W^{t_0}$ if

$$A_{vh}^{t_c} \cap A_{ob}^{t_c} \neq \emptyset \tag{3}$$

In practice, an algorithm must be devised to check whether the above condition holds true. This process can be simplified as follows. Let t_o be the time at which a collision prediction phase starts, and let the corresponding time window be W^{t_o}. Start by computing estimates of the centers of mass of the vehicle and obstacle, denoted $P_v(t) = (x_v(t), y_v(t))$ and $P_o(t) = (x_o(t), y_o(t))$, respectively, for $t \in W^{t_o}$. Assume, for simplicity of explanation, that the regions occupied by two moving bodies are inside two circles of radii R_{vh} and R_{ob}, and let $\epsilon = R_{vh} + R_{ob}$. Let $d(t) = ||P_v(t) - P_o(t)||$ be the estimated distance between the vehicle and the obstacle. A collision will not occur during the time window W^{t_o} if $d(t) \geq \epsilon, \forall t \in W^{t_o}$. In this case, no more calculations are needed and the execution of the Collision Prediction module (at the current step) is stopped. If (3) is violated, then a collision may occur and corrective actions must be taken, as explained in the next section.

4. COLLISION AVOIDANCE

Upon detection of a potential collision situation, the mechanisms for collision avoidance must be activated. In what follows we summarize briefly the methodology adopted for collision avoidance that is rooted in previous work reported in Carvalhosa et al. (2009), Kim Jin-Ho (1992), and Yun and Tan (1997).

In a dynamic environment, there are essentially two actions that a vehicle can take to avoid collisions: *i)* to spatially deconflict the paths of the vehicle and the obstacle by computing a new local path for the vehicle, or *ii)* to temporally deconflict the trajectories of the vehicle and the obstacle by acting on the vehicle's speed. In the present paper, the decision to opt for one of the above actions depends on the values of Δt_{ob}, which is defined as follows: Let B_{vh} and B_{ob} be the areas swept by the vehicle and the object, respectively during the time interval W^{t_0}. Further, let t_i and t_f in W^{t_0} be the initial and final instants of time of the interval in which B_{ob} intersects B_{vh}. If the estimated linear velocity of the target object is small (which means that the object is probably static) re-assign t_f to $t_f = t_0+\delta$, which is the final time in the window W^{t_0}. We define Δt_{ob} as $\Delta t_{ob} = t_f - t_i$ and impose the following rule: Let Δt_{thr} be an adjustable threshold. Action named *i)* is activated if $\Delta t_{ob} < \Delta t_{thr}$, while action named *ii)* is activated otherwise. This strategy captures the fact that if the projected paths of the vehicle and object overlap for a long period of time, then the safest approach is to locally deform the vehicle path. The sections that follow describe briefly actions *i)* and *ii)*.

4.1 Path re-planning using harmonic potential fields

The Potential field method, which will be used for online local path re-planning, consists of assigning an artificial potential field to the area where the vehicles operate. An attractive potential describes the goal position, while if there are obstacles in the area we assign them repulsive potentials. The new path can be derived from the gradient of the total artificial potential.

It is common for potential field methods to suffer from local minima. A local minimum can attract and trap the vehicle, preventing it from reaching its final goal. For this reason, harmonic potential fields are utilized by employing the panel method known in fluid mechanics. In this case, under suitable conditions (see Kim Jin-Ho (1992)) the harmonic function completely eliminates local minima, which eliminates the possibility of generating a stationary point in the velocity field except at the goal point. To this effect, all the potential functions used in the creation of the artificial field obey the Laplace equation $\nabla^2\phi = 0$, and can generate either attractive or repulsive potentials as follows:

$$\phi_g = \frac{\lambda_g}{2\pi}\ln(\sqrt{(x-x_g)^2+(y-y_g)^2}), \tag{4}$$

$$\phi_u = -U(x\cos\alpha + y\sin\alpha). \tag{5}$$

Equations (4) and (5) refer to the goal and uniform flow potential respectively, where (x_g, y_g) are the goal coordinates, α is the angle between the $x-axis$ and the direction of the uniform flow, and λ_g and U are the potentials strengths. Both potentials will drive the vehicle to its desired goal position. See Kim Jin-Ho (1992) for complete details.

Panel method

The panel method that has been used to solve the potential flow of a fluid around bodies of arbitrary shape is in this case used to derive an obstacle avoidance algorithm. The boundary of an obstacle in 2D space will be approximated by line segments (panels), each of them with source or sink singularities having a uniform density. The distributed singularities are used to deflect the oncoming stream so that it will flow around the body. The velocity potential at any point (x, y) in space caused by a panel j is

$$\phi_p = \frac{\lambda_j}{4\pi}\int_j \ln(R_j)dl_j$$

where $R_j = (x-x_j)^2 + (y-y_j)^2$, and λ_j is the strength of the source field per unit length. The overall potential created by an obstacle at a given point is the result of the net effect of all the panels that compose the obstacle frame i.e., $\phi_{ob} = \sum_{j=1}^{m}\phi_j$. The total artificial potential field is then given by

$$\begin{aligned}\phi_{total} &= \phi_g + \phi_u + \phi_{ob}\\ &= -U(x\cos\alpha + y\sin\alpha) + \frac{\lambda_g}{2\pi}\ln(\sqrt{R_g})\\ &\quad + \sum_{j=1}^{m}\frac{\lambda_j}{4\pi}\int_j \ln(R_j)dl_j \end{aligned}\tag{6}$$

A typical environment is illustrated in Fig. 4 where all the potentials are represented. Let $V_i > 0$ be the desired outward normal velocities at the center points of the panels

$$\frac{\partial}{\partial n_i}\phi(x_{ic}, y_{ic}) = V_i, \quad i = 1.2.....m \tag{7}$$

where n denotes a vector normal to the panel. Setting λ_g and U, the values of λ_j can be chosen so that inequality (7) is verified. The equations for λ_j's are derived in Kim Jin-Ho (1992) for a set of desired V_i. The values set for V_i do however need to be limited so that convergence to the goal position is guaranteed. As shown in Fig. 4, for large V_i's the vehicle might miss the goal. The m normal outward velocities V_i must be chosen such that, after solving (7), the following condition is satisfied

$$-\lambda_g > \sum_{i=1}^{m}\lambda_i L_i > 0 \tag{8}$$

The solution adopted in this paper is based on the work of Fahimi (2009) which provides a way to automatically compute a set m of V_i that satisfy inequality (8). The corresponding velocity field, $\mathbf{v} = (\dot{x}, \dot{y})$, is then derived from $\mathbf{v} = -\nabla\phi$ and using eq. (6), yielding

$$v_x(x,y) = U\cos\alpha - \frac{\lambda_g}{2\pi}\frac{\partial}{\partial x}\ln R_g - \sum_{j=1}^{m}\int_j \frac{\partial}{\partial x}\ln R_j dl_j$$

$$v_y(x,y) = U\sin\alpha - \frac{\lambda_g}{2\pi}\frac{\partial}{\partial y}\ln R_g - \sum_{j=1}^{m}\int_j \frac{\partial}{\partial y}\ln R_j dl_j$$

The resulting velocity vector $\mathbf{v} = (v_x, v_y)$ is characterized by its length $V = (\mathbf{v}^T\mathbf{v})^{\frac{1}{2}}$ and direction $\beta = \arctan(\frac{v_y}{v_x})$. Following $\mathbf{v}$ throughout the potential field will result in an obstacle free path.

4.2 Velocity correction

Velocity correction is applied when the detected trajectory intersections have a time span Δt_{ob} lower than the defined threshold Δt_{thr}. In this case, the obstacle can in principle be avoided by either increasing or decreasing the velocity of the vehicle. To this effect, recall first that in the set-up adopted for cooperative path following (see Ghabcheloo et al. (2009); Aguiar and Pascoal (2007)), the path to be traversed by the vehicle is parameterized by a scalar γ,

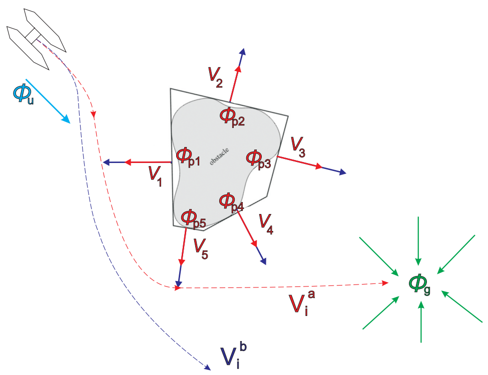

Fig. 4. Artificial potential field in a cluttered environment

and the speed along the path is always given in terms of the desired time-derivative of γ. The conversion from the latter to inertial speed is done by each vehicle at the path following level. As in the previous section, let t_i and t_f in W^{t_0} be the initial and final instants of time of the interval in which B_{ob} intersects B_{vh}. Let $P_v(t) = (x_v(t), y_v(t))$ denote the position of the center of mass of the vehicle at time t. Then, $P_v(t_0) = P_v(\gamma_0)$ and $P_v(t_i) = P_v(\gamma_g)$ for some values of γ_0 and γ_g. In the situation depicted in Fig. 6, collision is avoided if the vehicle will arrive at $P_v(\gamma_g)$ at time t_f. This is done by considering a virtual vehicle traveling along the path at a constant velocity V_d, such that at some desired instant of time $t_g \geq t_f$, the virtual vehicle will be located at a goal position $P_v(\gamma_g)$. The virtual vehicle velocity along the parameterized path is then given by

$$V_d = \frac{\gamma_g - \gamma_0}{t_g - t_0}$$

from which it follows that

$$\gamma_d(t) = \int_{t_0}^{t} V_d \, dt = V_d(t - t_0) + \gamma_0.$$

The objective is now to make the vehicle track this virtual vehicle. To this effect, let $e(t) = \gamma(t) - \gamma_d(t)$. Since $\dot{\gamma} = v$, it follows that and $\dot{e}(t) = v(t) - V_d$. Thus, by setting

$$v = V_d - k(\gamma - \gamma_d), \quad k > 0$$

it can be concluded that with the above control law $\dot{e} = -ke$, that is, the γ- tracking error converges to zero exponentially and collision will be avoided.

4.3 Right of Way

It is important to remark that the issue of collision avoidance bears close connection with classical rules for right of way during maneuvers at sea. This topic deserves attention but will not be studied in detail here. Notice however that the primary drive for the vehicle is to give right of way to an obstacle, that is, once an obstacle is detected and labeled as dynamic, the vehicle will take the safest approach, which is to decrease velocity and let the obstacle pass, resuming the velocity profile set for the mission once collision avoidance is guaranteed. The only exception to this behavior will occur in the presence of another automated vehicle, possibly a team member. In this scenario, priority will be issued to the vehicle traveling on a starboard track.

5. SIMULATION RESULTS

The performance of the algorithms described in the previous sections was assessed through Matlab simulations. First, the individual modules described were analyzed. The overall cooperative path following / collision avoidance system was then tested by resorting to a new simulator named NetMarSys (Networked Marine Systems Simulator) developed at ISR/IST. Fully supported on Simulink and Matlab, the simulator models the key different aspects of cooperative multiple vehicle systems. All simulations relate to the application of the Collision Avoidance system to Autonomous Surface Craft (ASC), for which the path-following controllers described in Maurya P. (2009) were used.

Fig. 6 shows collision prediction between the ASC and an incoming dynamic obstacle. The targets position is fed directly into the Interactive multi model Kalman filter (IMMKF) once every second, with a zero mean Gaussian additive error. The linear and angular estimated velocities of the target, $\omega = 0.0312$ and $v = 1.5723$, respectively returned by the IMM-KF are used to derive a probable trajectory for the obstacle. An intersection of paths is detected for a time span larger than the defined $\Delta t_{treshold} = 15s$, resulting in the creation of a Static Virtual Obstacle that can later be used to compute an alternative path.

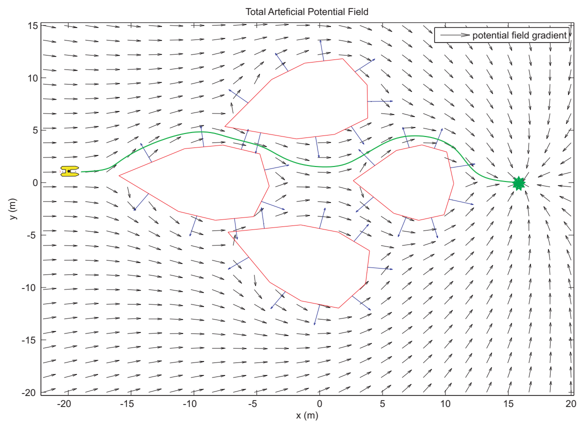

Fig. 5. Path Planing in a cluttered environment: gradient of the potential field

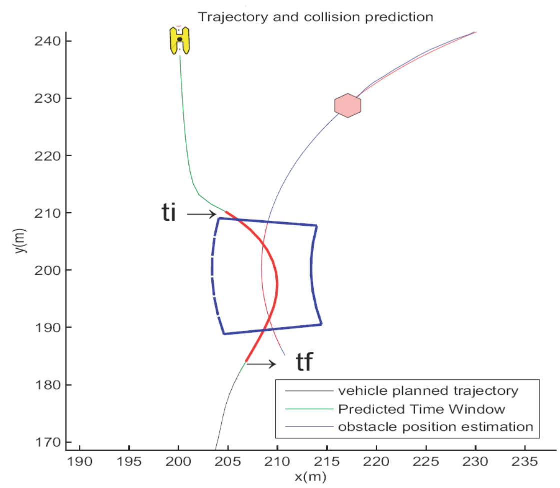

Fig. 6. Simulation results for the Collision Prediction module: tracking of a dynamic obstacle

Fig. 7 shows the implementation of the Collision Avoidance System for a team of three ASC performing a path-following mission. In this scenario, two of the team members perform path re-planing to avoid collision with the

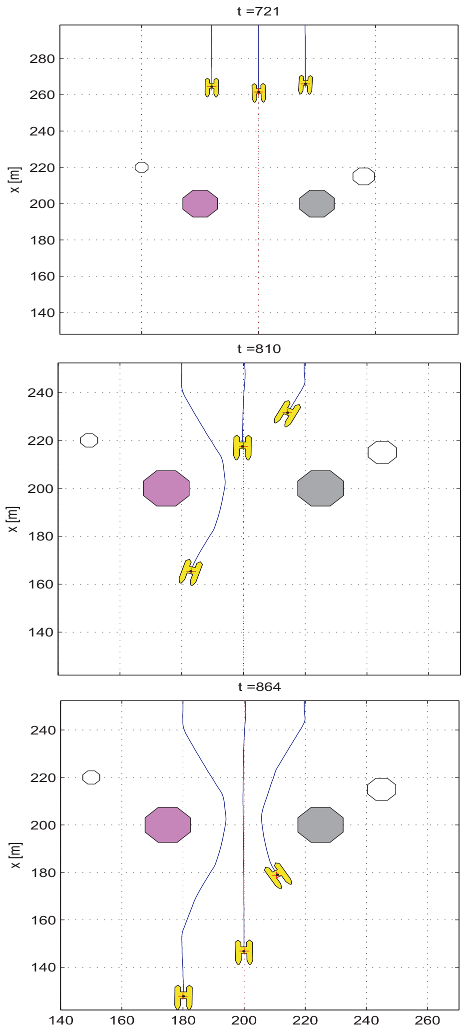

Fig. 7. Team of vehicles facing a bottleneck situation, where velocity control is used to achieve coordination

obstacles and reach a "bottleneck" situation; velocity control comes into play to prevent inter-vehicle collisions. The team moves past the bottleneck in a coordinated manner.

6. CONCLUSIONS

The paper proposed a collision avoidance system for autonomous vehicles working in dynamic environments. To integrate collision avoidance in a typical cooperative motion control (CMC) architecture, an hierarchical structure was devised. This approach allows for a team of autonomous vehicles to maneuver cooperatively and avoid collisions. The problem was decoupled into a collision prediction stage and a corresponding collision avoidance maneuver. Prediction is realized by first estimating the target's velocity through the use of an Interactive multi model Kalman filter, and then deriving its probable trajectory within a given time window. Two strategies were then devised to avoid collision: Path re-planing based on harmonic potential field theory, or by controlling the speed of each of the vehicles along their assigned mission path. The efficiency of the solutions was illustrated in simulation. Two key issues will be addressed in future work: 1) optimal trajectory re-planning by taking into account energy consumption or other mission-related constraints, and ii) implementation and testing of selected obstacle avoidance algorithms at sea.

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