Predictive Dynamic Collision Avoidance of Unmanned Surface Vehicles Using Behavior-Based Method in Maritime Environment

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December 25, 2020

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***Abstract*—A good ability of the dynamic collision avoidance (DCA) is essential for the unmanned surface vehicle (USV), which is the focus of this paper. Since current research mainly uses real-time navigation information to achieve collision avoidance to other vessels, however, in the realistic maritime environment, USV can rarely obtain such real-time information through automatic identification system (AIS) or other equipment. So, in this paper, a Kalman filter-based predictive dynamic collision avoidance of unmanned surface vehicles is proposed using the behavior-based method. The Kalman filter (KF) is integrated into the USV planner to predict the trajectories of other obstacle ships and several behaviors are designed in the light of the International Regulations for Preventing Collisions at Sea (COLREGs) to implement collision avoidance. Simulations involving three moving obstacle vessels with changing navigational statuses are presented and realistic broadcasting intervals of a class A AIS device are used in the simulation to indicate that the Kalman filter can reasonable predict the positions of moving obstacle ships and the USV can effectively make obstacle avoidance behaviors that meet the requirements of the COLREGs.**

Keywords- unmanned surface vehicle (USV); dynamic collision avoidance (DCA); Kalman filter (KF); COLREGs

I. INTRODUCTION

Unmanned surface vehicle (USV) is a type of intelligent system that sails on the water, which has been increasingly used in military and civilian fields such as port patrol, search and rescue, marine environment monitoring, seabed resource detection, and so on. In recent years, an increasing number of scholars have studied how to use USV instead of manned ships to perform tasks.

Collision avoidance (CA) is an essential part of the USV control system, which can ensure the safety of the USV during the execution of the task. There are a variety of approaches involving collision avoidance, such as A* algorithm [1], potential field method [2,3], fuzzy logic [4], evolutionary algorithm [5], particle swarm optimization [6], velocity obstacle [7], fast marching method [8], reinforcement learning[9,10] and so on. Among these approaches, the behavior-based method is also a popular solution dealing with the CA problem, which is widely studied for mobile robotic applications [11,12].

The essence of the behavior-based method is motivated by natural collective phenomena [13], which is useful to guide the unmanned system in an unknown or dynamically changing environment [14]. As for the USV, when performing tasks, the environment it is in also keeps changing. The USV needs to obtain information about the surroundings through the onboard sensing devices, such as radar or AIS, to make effective obstacle avoidance. Therefore, behavior-based method can be used to guide USVs to avoid obstacles. Meanwhile, when the USV sails at sea, all its actions must comply with the International Regulations for Preventing Collisions at Sea (COLREGs). Using behavior-based method, the COLREGs can be easily integrated into the process of designing behaviors and the USV can effectively perform CA actions prescribed by the COLREGs.

The CA problem of the USV has been well studied by many scholars, however, most of these studies assume that USV has a robust communication channel and the real-time navigation states of other ships can be easily obtained. While, this situation is unrealistic in a maritime environment. In the actual navigation, the USV mainly uses the AIS to obtain information of other vessels. The AIS is a broadcasting mechanism that broadcasts the navigation information at regular intervals. At the broadcasting point, the USV can obtain the quasi-real-time navigation states of other ships, however, no information can be obtained during the waiting period. To some extent, the USV is “blind” at this stage. So, how to deal with this problem in the realistic maritime navigation of the USV is also a focus of this paper.

There are two main contributions of this paper: 1) the COLREGs-integrated behaviors are designed to guide the USV to tackle the dynamic collision avoidance (DCA) problem and 2) the Kalman filter (KF) is incorporated into the behavior-based method to predict the trajectories of other obstacle ships during the data waiting period of the AIS.

And the remainder of this paper is organized as follows: after this “Introduction”, the broadcasting mechanism of AIS and the fundamentals of Kalman filter algorithm are explained in section II. Details of the COLREGs-integrated behaviors and the predictive dynamic collision avoidance (PDCA) based on behaviors method are given in section III. In order to verify the PDCA approach proposed in this paper, computer-based simulations are shown in section IV and conclusions are drawn in section V.

II. PRELIMINARY KNOWLEDGE AND PROBLEM STATEMENT

A. Motion Model

The planar motion model of vessels used in this paper is formulated as follows:

$$\begin{cases} \dot{x} = u\cos\psi - v\sin\psi \\ \dot{y} = u\sin\psi + v\cos\psi \\ \dot{\psi} = r \\ \dot{u} = \dfrac{1}{m_{11}}\left[m_{22}vr - d_u u - d_{|u|u}|u|u + \tau_u \right] + \xi_u \\ \dot{v} = \dfrac{1}{m_{22}}\left[m_{11}ur - d_v v - d_{|v|v}|v|v \right] + \xi_v \\ \dot{r} = \dfrac{1}{m_{33}}\left[(m_{11} - m_{22})uv - d_r r - d_{|r|r}|r|r + \tau_r \right] + \xi_r \end{cases} \tag{1}$$

where $[x, y]^{\mathrm{T}}$ is the position vector and ψ is the heading angle of the ship defined in the earth-fixed coordinates O_E-X_EY_E. $[u, v]^{\mathrm{T}}$ is the linear velocity vector and r is the angular velocity given in the body-fixed frame O_b-X_bY_b of the vessel. These two coordinates are shown in Fig.1.

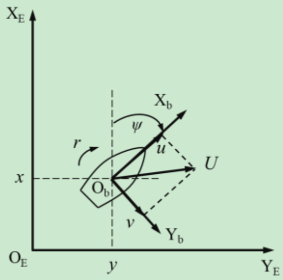


Figure 1. Illustration of the motion model.

m_{11}, m_{22} and m_{33} denote inertial masses. d_u, $d_{|u|u}$, d_v, $d_{|v|v}$, d_u and $d_{|r|r}$ represent hydrodynamic damping terms. $[\tau_u, \tau_r]^{\mathrm{T}}$ is the control input vector which is composed of the surge force τ_u and the yaw moment τ_r. ξ_u, ξ_v and ξ_r denote the time-varying disturbances, which are used to simulate the environmental influence caused by winds, waves and currents when the ship sails at sea. These disturbance terms, which are given in (2), are added to the motion model to improve the robustness of the overall system when it is used in the actual navigation.

$$\begin{cases} \xi_u = h(s)w_u(s) \\ \xi_v = h(s)w_v(s) \\ \xi_r = h(s)w_r(s) \end{cases} \tag{2}$$

where $h(s)$ is a second-order transfer function and terms $w_u(s), w_v(s), w_r(s)$ are defined as

$$w(s) \sim N\left(0, \sigma^2\right) \tag{3}$$

which is a zero-mean Gaussian white noise to model the uncertain disturbance.

B. AIS Broadcasting Mechanism

Automatic identification system (AIS) is a type of navigation aid system that is applied to the maritime safety and communication between ship and shore, or between different ships. AIS is a broadcasting mechanism that is shown in Fig.2. Ships equipped with AIS can transmit their own navigation information by broadcasting at fixed time intervals and receive other ships' information.

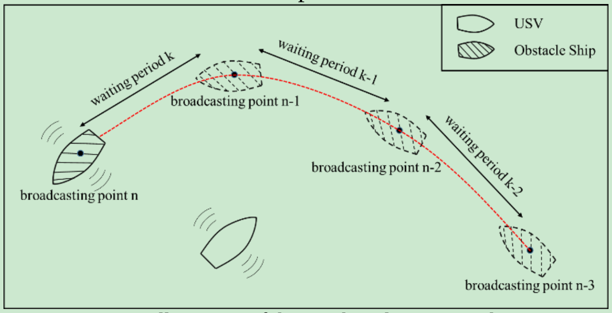


Figure 2. Illustration of the AIS broadcasting mechanism.

There are two phases during the AIS broadcasting, i.e. the waiting period and the broadcasting point. The AIS broadcasts the ship its own navigation information at the broadcasting point and the other vessels can be aware of her. However, during the waiting period, no data is transmitted via AIS. So other vessels cannot perceive its existence. Time interval between two broadcasting points varies with the type of the AIS and the navigation states of vessels, and for class A AIS, time intervals are listed in Table I.

TABLE I. TIME INTERVALS OF CLASS A AIS

Ship's navigation states	Nominal time intervals
Ship at anchor or moored and not moving faster than 3 knots	3 min
Ship at anchor or moored and moving faster than 3 knots	10 s
Ship 0-14 knots	10 s
Ship 0-14 knots and changing course	3 s
Ship 14-23 knots	6 s
Ship 14-23 knots and changing course	2 s
Ship moving faster than 23 knots	2 s
Ship moving faster than 23 knots and changing course	2 s

When the USV sails at sea, it cannot obtain the navigation information of other vessels through AIS during the waiting period. While at the broadcasting point, the data received by the USV via AIS has signal noise. In order to improve the accuracy of the received obstacle ship's navigation information and apply it to DCA problem of the USV, the Kalman filter algorithm is used in this paper.

C. Kalman Filter Algorithm

Kalman filter (KF) algorithm is currently the most widely used filter method, and it has been better used in communication, navigation, guidance, control and other fields. KF is a recursive estimation algorithm which has two main processes, i.e. the prediction process and the update process.

In the prediction process, the system state vector $\hat{x}_{t|t-1}$ at time step t is predicted by the KF using the state at previous step t-1. And the system covariance matrix $P_{t|t-1}$ is also calculated.

$$\begin{cases} \hat{x}_{t|t-1} = A_t \hat{x}_{t-1|t-1} + B_t u_t \\ P_{t|t-1} = A_t P_{t-1|t-1} A_t^T + Q_t \end{cases} \tag{4}$$

where A_t is the state transition matrix, B_t denotes the control input matrix and u_t is the control input. Q_t represents transition noise in this process.

Then the KF gain K_t for time step t is calculated based on the system covariance matrix $P_{t|t-1}$.

$$K_t = P_{t|t-1} H_t^T \left(H_t P_{t|t-1} H_t^T + R_t \right)^{-1} \tag{5}$$

where H_t is the observation matrix and R_t is the observation noise.

Afterwards, the system state and the covariance matrix estimated in the prediction process are updated using the observation Z_t to filter out the noise in the update process.

$$\begin{cases} \hat{x}_{t|t} = \hat{x}_{t|t-1} + K_t \left(Z_t - H_t \hat{x}_{t|t-1} \right) \\ P_{t|t} = \left(I - K_t H_t \right) P_{t|t-1} \end{cases} \tag{6}$$

Finally, the system state and the covariance matrix with the improved accuracy obtained in the update process are passed back to the prediction process for next time step t+1.

As for the navigation of the USV, when there is no AIS data, the prediction process of the KF is used to estimate the trajectory of the obstacle ship (OB). And at the broadcasting point, the update process is employed to filter the signal noise of the received information and update the position of the OB. So, the USV can be aware of the OB at any time since it was first perceived by the USV. The illustration of KF prediction process is shown in Fig.3.

The USV system state vector x_t is given as

$$x_t = \left[x, u, y, v, \psi \right]^T \tag{7}$$

According to the constant velocity model (CVM) [15], the state transition equation of the USV can be expressed as

$$x_{t+1} = A_t x_t + Q_t \tag{8}$$

where state transition matrix A_t is

$$A_t = \begin{bmatrix} 1 & \Delta t & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & \Delta t & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{9}$$

where Δt is the time step and the transition noise Q_t is defined as

$$Q_t \sim N\left(0, q\right) \tag{10}$$

and

$$q = diag\left(0.5\Delta t^2, \Delta t, 0.5\Delta t^2, \Delta t, \Delta t\right) \bullet \sigma_Q^2 \tag{11}$$

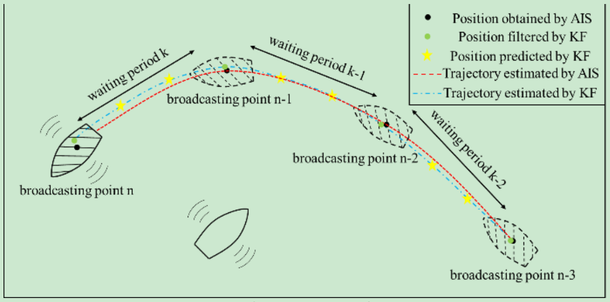


Figure 3. Illustration of the Kalman filter prediction process.

In the DCA problem of the USV, the observation is defined as $Z_t = \left[x, y, \psi \right]^T$ and the observation equation is expressed as

$$Z_t = H_t x_t + R_t \tag{12}$$

where the observation matrix H_t is

$$H_t = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{13}$$

and the observation noise R_t is given as

$$R_t \sim N\left(0, \sigma_R^2\right) \tag{14}$$

Based on state transition equation (8) and the observation equation (12), the KF algorithm can be used to predict trajectories of other ships during the navigation of the USV.

III. PREDICTIVE DYNAMIC COLLISION AVOIDANCE USING BEHAVIOR-BASED METHOD

A. *COLREGs-integrated Behaviors*

COLREGs are maritime traffic rules that all vessels sailing at sea must abide by, which include 41 rules to ensure the safety of vessels [16]. According to COLREGs, collision situations between ships are shown in Fig.4.

In the light of angle α shown in Fig.4, which is the relative azimuth angle between the USV and the OB defined in the body-fixed frame O_b-X_bY_b of the USV, collision situations can be divided into 4 situations (Table II)

TABLE II. COLLISION SITUATIONS

Situations	Conditions
Head-on	$\alpha \in \left(0°, 15°\right] \cup \left(345°, 360°\right]$
Crossing from right	$\alpha \in \left(15°, 112.5°\right]$
Overtaking	$\alpha \in \left(112.5°, 247.5°\right]$
Crossing from left	$\alpha \in \left(247.5°, 345°\right]$

Among all rules defined in COLREGs, there are 5 rules, i.e. rules 13-17, involve the relevant requirements of collision avoidance between vessels. Based on these 5 rules, several behaviors, which are listed in Table III, are designed to guide the USV to avoid other moving obstacle ships.

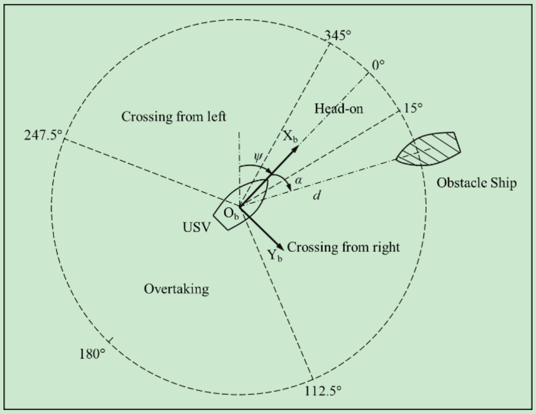


Figure 4. Illustration of collision situations.

TABLE III. COLLISION AVOIDANCE BEHAVIORS

Situations	Behaviors
Head-on	Turn right 30° to pass the obstacle ship on her portside
Crossing from right	Turn right 30° based on α to bypass the obstacle ship on her stern
Overtaking	The turning angle is designed to 30° opposite to the heading of the obstacle ship
Crossing from left	USV is “stand-on” vessel and should keep her navigation state

B. Predictive DCA based on Behaviors Method

TABLE IV. ALGORITHM

Algorithm 1: Predictive dynamic collision avoidance based on behaviors
input: AIS data, planned path of USV
initialization: States of USV, parameters of KF algorithm
while USV does not arrive at the destination
for every obstacle ship (OB) in the detection range of USV
if at AIS broadcasting point
AIS data is received, update the state of OB using (6)
else
in the waiting period, predict the state of OB using (4)
calculate KF gain using (5)
end if
calculate distance between USV and OB
end for
find the nearest OB
calculate DCPA and TCPA between USV and the nearest OB
if $DCPA<DCPA_{threshold}$ and $TCPA< TCPA_{threshold}$
there is a collision risk
COLREGs-integrated behaviors are adopted by USV to avoid OB
else
there is no collision risk
LOS law in the light of the planned path of USV is adopted
end if
desired heading angle ψ of USV is obtained
new state of USV is updated using planar motion model (1)
end while

In order to improve the feasibility of the COLREGs-integrated behaviors designed before to guide the USV to avoid collision between moving ships in the realistic maritime environment using AIS, the KF algorithm aforesaid is incorporated into the planner of the USV to predict trajectories of obstacle ships (OBs) during waiting period and filter the noise of the AIS data at the broadcasting point. The estimated states by KF algorithm are used as inputs of the COLREGs-integrated behaviors to achieve collision avoidance of the USV. So we named it predictive DCA based on behaviors method. The flowchart of this method dealing with the DCA problem of the USV is shown in Fig.5.

The pseudocode of the proposed predictive DCA based on behaviors method is shown in Table IV.

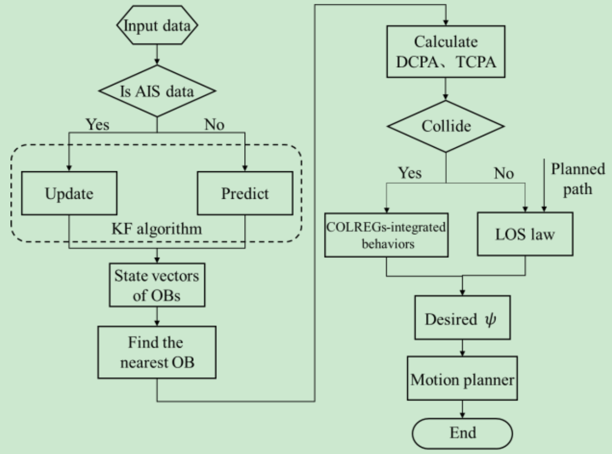


Figure 5. Flowchart of the predictive DCA based on behaviors method.

IV. ALGORITHM SIMULATION

To verify the proposed PDCA based on behavior method, the computer-based simulation is employed in this section.

The sailing trajectory of the USV under the given planned path is shown in Fig.6.

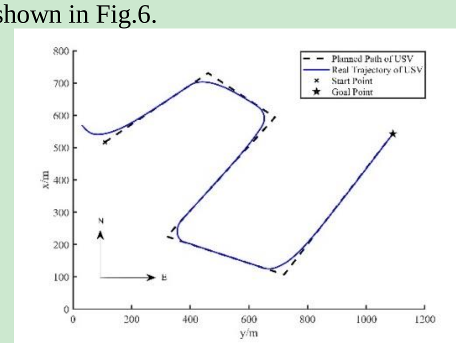


Figure 6. Trajectory of USV under given planned path.

Three moving obstacle ships, i.e. OB1, OB2 and OB3, are added in the sailing area of the USV, and trajectories of these four vessels are given in Fig.7.

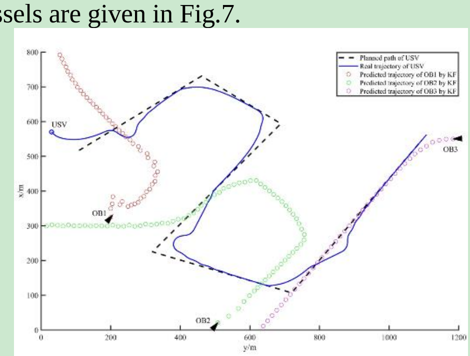
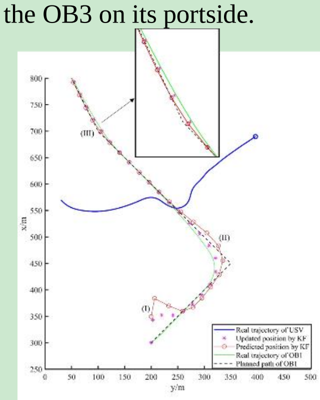


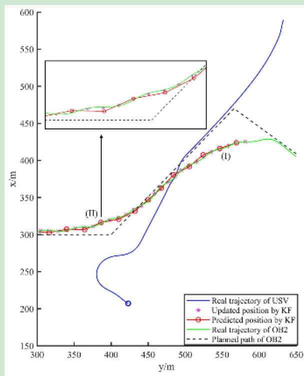
Figure 7. Trajectories of USV and other three obstacle ships.

In order to see the collision avoidance processes of USV and three OBs more clearly, three detailed subplots are shown in Fig.8.

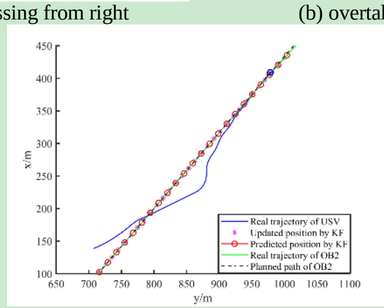
These subplots describe three collision situations, in which the USV is required to take avoidance behaviors initiatively. As shown in Fig.8, the behaviors designed in the paper can effectively make the USV perform avoidance maneuvers in compliance with the COLREGs under different collision situations. In the case of “crossing from right”, the USV turns right to bypass the OB1 on its stern. While in the situation of “overtaking”, the USV turns left opposite to the heading of the OB2 that points to the right. When the USV and the OB3 meet each other on reciprocal courses, the USV turns right to pass the OB3 on its portside.



(a) crossing from right



(b) overtaking



(c) head-on

Figure 8. Detailed subplots of CA between USV and OBs.

And the effect of the KF algorithm to estimate the trajectories of OBs are also reflected in Fig.8. In addition to the initial stage of the simulation and situations in which there are obvious changes in the navigation status of OBs, the proposed PDCA method has a good prediction effect on the trajectories of OBs. Based on the predicted positions, the USV still has a good DCA ability during the overall maritime navigation.

V. CONCLUSIONS

The predictive dynamic collision avoidance (PDCA) using behavior-based method of the USV is proposed in this paper. Behaviors in compliance with the COLREGs are designed to guide the USV to avoid the moving obstacle ships in the maritime navigation. Moreover, to deal with the problem that the USV cannot receive the AIS data during the waiting period and to filter out the signal noise that exists in the AIS data at the broadcasting point, the Kalman filter algorithm is incorporated into the behavior-based method. The effectiveness of the proposed algorithm in the USV dynamic obstacle avoidance is verified by the computer-based simulation.

ACKNOWLEDGMENT

This work is supported by the National Natural Science Foundation of China (No. 51509055 and No. 51409054). The authors also gratefully acknowledge the helpful comments and suggestions of the reviewers, which have improved the presentation.

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