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ERROR MITIGATION ALGORITHM BASED ON BIDIRECTIONAL FITTING METHOD FOR COLLISION AVOIDANCE OF UNMANNED SURFACE VEHICLE

Lifei Song[1, 2]
Zhuo Chen[2]
Yunsheng Mao[2]
Zaopeng Dong[2]
Zuquan Xiang[2]
[1] School of Transportation, Wuhan University of Technology, Wuhan, China
[2] Key Laboratory of High Performance Ship Technology (Wuhan University of Technology) Ministry of Education, Wuhan, China

ABSTRACT

Radars and sensors are essential devices for an Unmanned Surface Vehicle (USV) to detect obstacles. Their precision has improved significantly in recent years with relatively accurate capability to locate obstacles. However, small detection errors in the estimation and prediction of trajectories of obstacles may cause serious problems in accuracy, thereby damaging the judgment of USV and affecting the effectiveness of collision avoidance. In this study, the effect of radar errors on the prediction accuracy of obstacle position is studied on the basis of the autoregressive prediction model. The cause of radar error is also analyzed. Subsequently, a bidirectional adaptive filtering algorithm based on polynomial fitting and particle swarm optimization is proposed to eliminate the observed errors in vertical and abscissa coordinates. Then, simulations of obstacle tracking and prediction are carried out, and the results show the validity of the algorithm. Finally, the method is used to simulate the collision avoidance of USV, and the results show the validity and reliability of the algorithm.

Keywords: Unmanned Surface Vehicle; Position prediction; Error mitigation; Autoregressive model; Particle Swarm Optimization

INTRODUCTION

An Unmanned Surface Vehicle (USV) is a ship that navigates on water in an autonomous manner. Its autonomous collision avoidance capability is the basis for safe navigation and undertaking maritime tasks [1]. A USV uses the Automatic Identification System (AIS) and radars to access environmental information [2]. Among them, radars are the basic devices for USV to obtain obstacle information [3]. The International Maritime Organization (IMO) specifies that the maximum ranging error of radar should be 1% of the range or 30 m and that the azimuth error should be within 1° [4]. However, radars present unstable accuracy because of the complexity of sea conditions and existence of clutters and exhibit unacceptable detection errors [5]. Given that the collision avoidance planning of USV is based on the accurate tracking of obstacle targets [6], the errors of the latter may significantly affect the result of the former [7].

The estimation and prediction of position, velocity, and information for maneuvering target are important issues in target tracking area and are closely relevant to information fusion [8]. Boats, which may suddenly change their acceleration and turning, are principal obstacles that can be difficult to avoid for USVs. For an effective target tracking, the motion of target should be modeled first and then the state of target should be estimated by filtering [9]. However, the filter and motion models of target are often mismatched owing to the uncertainty and variability of motion modeling, thereby degrading the effect of estimation [10]. Therefore, filtering the motion data of target by using a simple algorithm, weakening the influence of observation error, and accurately estimating the target motion are crucial tasks in maneuvering target tracking technology [11].

The Wiener filtering method tracks a target on the basis of input signals and noises, and this method has significantly contributed to the application and development of filter theory. The effect of filtering degrades when the priori information deviates from the hypothesis [12]. Widrow and Hoff [13] of the Stanford University proposed the least mean squares adaptive algorithm based on the Wiener filter and Kalman filter (KF) theory and laid the foundation of adaptive filtering theory [14]. Compared with the Wiener filtering, this algorithm can adjust the parameters of the filter by self-learning without knowing the prior information of input signals and noises and can thus obtain optimal estimation. However, the effect of adaptive filtering is difficult to be controlled [15]. Unlike the traditional Wiener filtering and KF algorithms, algorithms based on the least squares criterion, such as th recursive least squares method [16], and QR decomposition of the minimum method, regard the minimum squared error sum as the optimization target. However, the principle of the methods determines that they can only be applied in the estimation or approximation of long-term statistical properties. Singer [17] proposed a time-dependent model (the Singer model) that assumes noises as colored and considers the targeted acceleration to be a uniform time-dependent process, the process is subject to a zero-mean uniform distribution. However, the model causes large errors for maneuvering target, thereby leading to an undesirable result of estimation. The Jerk model algorithm that considers the order of the state vector derivative as the main reason that affects tracking performance, and the Jerk term (acceleration rate) are introduced into a system model to achieve an accurate estimate of acceleration [18]. However, when the input Jerk term is a step transition, the model algorithm produces some definite steady-state errors. The model parameters also cannot be adjusted adaptively with the change in the target maneuverability, thereby affecting the tracking accuracy of the algorithm. The interacting multiple model has been developed to a complete interactive multi-model algorithm on the basis of the generalized pseudo-Bayesian algorithm. The model has also been combined with cubature KF [19] or linear quadratic regulator [20]. To obtain an ideal effect, the model needs a wide range of maneuvering forms. This requirement means a substantial increase in computing.

The advantages and limitations of the above-mentioned methods are listed in Table 1.

The autoregressive model is a convenient prediction algorithm that describes variables at later times with the linear combination of variables given in advance [21]. The unfiltered information for target obtained by the autoregressive model results in great perturbations. To solve the problem, a computationally fast algorithm for filtering is proposed in this study in consideration of the requirements of timeliness in the avoidance of USV. First, the sampling points of target are fitted as a polynomial curve by using the least squares method to reduce the longitudinal errors. Thereafter, an improved Particle Swarm Optimization (PSO) algorithm is used to fit the horizontal data of sampling position on the basis of the modified curve. A penalty function is introduced in the PSO algorithm to limit the fitting range and thus keep all the modified points in a reasonable area. After the bidirectional fitting, the radar errors can be effectively reduced. The proposed algorithm can be used in the collision avoidance of USVs.

The paper is organized as follows. In Section 1, the autoregressive model is introduced and the problem of the significant effect of detection errors on the accuracy of motion prediction is analyzed. In Section 2, an error mitigation algorithm based on the bidirectional fitting method that uses polynomial and Particle Swarm Optimization [22] is proposed. In Section 3, simulations of trajectory prediction and obstacle avoidance are carried out, and the results are analyzed in detail to verify the effectiveness of the algorithm. Finally, conclusion is remarked in the last section.

PROBLEM FORMULATION

We predict the moving position using the autoregressive model.

We assume that, at moment t, the position of obstacle is $p(t)$, $p = (x\ y)^T$. After the obstacle enters the detection area of radar, the continuous position sequence of this obstacle can be obtained.

Tab. 1. Schematic diagram of mass point

Methods Name	Advantages	Limitations
Wiener filtering method	It can be used in continuous and discrete models	The effect of filtering degrades when the priori information deviates from the hypothesis
Least mean squares (LMS) adaptive algorithm	It can adjust the parameters of the filter by self-learning without knowing the prior information of input signals and noises	The effect of adaptive filtering is difficult to be controlled
Recursive least squares method	It can converge much faster than the LMS algorithm	It can only be applied in the estimation of long-term statistical properties
Singer model	It is a global statistical model and can be used for filtering in various tracking methods	The model causes large errors for high maneuvering target. Inaccurate noise statistics can also cause low precision
Jerk model	It improves the accuracy by adding the jerk dimension to the matrix compared with the single model	The model parameters cannot be adjusted adaptively. It takes more time to stabilize than the single model
Interacting multiple model	It can efficiently adjust the probability of model	It requires a large amount of computation

Given the inertia of moving object, the current position of obstacle is assumed related to its former n positions; this relationship complies with the n-order autoregressive model as follows:

$$p(t)=\sum_{i=1}^{n}\alpha_i p(t-i)+e(t), \tag{1}$$

where n is the order of the autoregressive model, $e(t)$is the position prediction error, and $\alpha_i$is the regression coefficient. The type of regression coefficient depends on the degree of association between two directions of motion target. A scalar α_i enables synchronous alteration between the x and y velocity. A diagonal matrix α_i enables independent alteration between the x and y velocity. If α_i is a two-dimensional matrix, then the x and y velocity are partial interactional.

Considering the motion characteristics of objects at sea, we assume that the acceleration of obstacle changes slowly. This condition can be described using the first-order autoregressive model as follows:

$$a(t) = \beta_i a(t - i) + w(t), \tag{2}$$

where β_i denotes the regression coefficient and $w(t)$ denotes the acceleration prediction error. From the relationship between acceleration and position, we obtain

$$a(t) = p(t) - 2p(t - 1) + p(t - 2), \tag{3}$$

where $a(t)$ is the acceleration at time t. From Equations (2) and (3), the obstacle position at moment $t + 1$ can be expressed as

$$p(t + 1) = (2 + \beta_t)p(t) - (2\beta_t + 1)\, p(t - 1)+ \beta_t p(t-2) + w(t), \tag{4}$$

During the obstacle avoidance planning of USV, the predictions of target movements in multiple cycles are needed. The obstacle position of step k at moment t is obtained using the mathematical induction method as follows:

$$p(t+k)=p(t)+kv(t)+(\sum_{i=1}^{k}(k+1-i)\prod_{1}^{i}\beta_{i-1})a(t) \tag{5}$$

where $v(t)$ is the velocity at time t and $v(t) = p(t) - p(t-1)$. To fit the first-order autoregressive model of acceleration by using the least squares method, we assume

$$\beta_i=\left\{\beta \mid min\left(\sum_{j=4+i}^{N+j}[a(j)-\beta a(j-1)]^T[a(j)-\beta a(j-1)]\right)\right\} \tag{6}$$

where the function $min(x)$ is the minimum of x; N is the number of the foregone motion data, which are used to predict the dynamic positions of obstacle. When the value of N is large, a large amount of historical data are needed and the effect of pre-movements on the predicted position is significant; this condition is suitable for predicting slow moving objects. When the value of N is small, a small amount of the historical data are needed and the future positions of the obstacle depends mainly on the recent movements of the object; this condition is less constrained by the previous movement and suitable for predicting fast moving objects.

We can find from Equation (5) that, at time t, the predicted difference in positions between two consecutive periods k and $k + 1$ is

$$\Delta p(t+k+1)=v(t)+(\sum_{i=1}^{k+1}\prod_{1}^{i}\beta_{i-1})a(t) \tag{7}$$

Equation (7) shows that the difference is closely related to the prediction step k and the acceleration. When the value of k is large, the difference is significant because of the coefficient before $a(t)$. The acceleration of ships at sea often presents a slight change. However, the changes may be significantly magnified with data errors, thereby leading to a remarkable increase in the difference and thus large errors in the multi-step prediction.

A simulation for analyzing the above-mentioned problem is shown in Fig. 1. In the simulation, the obstacle presents an error within the standard range of radar error. The prediction positions are obtained using Equations (5)–(6). The parameters are set as $N = 6$ and $k \in [1, 2, 3, 4]$. In particular, no prediction positions are applied at the first six times. Thereafter, six foregone observation positions are needed for prediction, and the first to fourth future positions are forecasted at each moment. The obstacle moves from the left corner. Even in the case of small disturbance of the observed data, the prediction results do not maintain motion inertia but show a great fluctuation. Specifically, when the value of k is large, the difference between the predicted position and the actual position is significant. The effect is highly pronounced when the trajectory changes in a large degree.

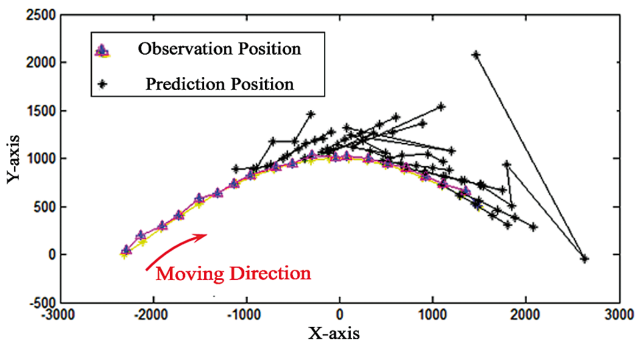


Fig. 1. Obstacle trajectory prediction with observation error

We conclude from the theoretical derivation and simulation results above that, if the observation error of obstacle is ineffectively reduced, then the accuracy of motion prediction cannot be guaranteed and thus the collision avoidance planning of USV may fail. Therefore, the observed data should be modified to reduce the acceleration change caused by radar errors and obtain a smooth trajectory that is close to the actual one.

ERROR MITIGATION METHOD BASED ON POLYNOMIAL AND PSO

Considering the radar observation error, the obstacle observation position is randomly distributed within the circle with *r_error* = 30, as specified by IMO. We select *N* sampling coordinates from the obstacle observation data at moment *t* by a sampling period of $T_p(k)$. The value of $T_p(k)$ is given as follows:

$$T_p(k) = \left\lfloor \frac{R_w}{10\max(\boldsymbol{v}_k)} \right\rfloor T \tag{8}$$

where R_w is the radius of the radar observation scope and T is the observation period of the radar. $\boldsymbol{v}_k$ is the relative velocity set of various periods between the USV and the *k*th obstacle. In particular, $\boldsymbol{v}_k = \{\boldsymbol{v}_{k,1}, \boldsymbol{v}_{k,1}, \ldots \boldsymbol{v}_{k,n}\}$. The mathematical symbol $\lfloor x \rfloor$ indicates that the real x is rounded down. Equation (8) shows that $T_p(k)$ is a positive integer multiple of T, and the value of T_p differs with different obstacles. When the radar scanning cycle is short and the relative speed of USV and obstacle is relatively small, the radar observation errors may misalign the observation positions of obstacles in several near scanning cycles *T*. As a result, the motion of obstacles can be difficult to detect and the errors can be difficult to distinguish and eliminate. Ultimately, the trajectory prediction of obstacles becomes difficult. Thus, the prediction period $T_p(k)$ is adopted for reasonably increasing the data sampling period and improving the accuracy of error elimination.

Given that the polynomial fitting is unidirectional, a local coordinate system $x'Oy'$ is established with *N* sampling points. The error mitigation is performed in the local coordinate system, and the coordinate conversion is expressed as

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos(\alpha) & \sin(\alpha) \\ -\sin(\alpha) & \cos(\alpha) \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \tag{9}$$

where α is the rotation angle between the local coordinate system and global coordinate system.

1. **Error mitigation in vertical coordinates with polynomial fitting method.**
   We fit the sampling points (x', y'_i) with the polynomial as follows:

$$p_n(x'_i) = a_0 + a_1 x'_i + a_2 x'^2_i + \ldots + a_k x'^k_i \tag{10}$$

   where p_n0 is the function of the polynomial fitting curve; a_0, a_1, a_2, and a_1 are the coefficients of the function. The least squares method is used in the fitting.

   The value of the polynomial coefficients can be obtained by solving the extreme of *I* in the following equation:

$$I = \sum_{i=0}^{m} [p_n(x_i^{'}) - y_i^{'}]^2 = \sum_{i=0}^{m} [\sum_{k=0}^{n} a_k x_i^{'k} - y_i^{'}]^2 \tag{11}$$

   The points on the curve are fitted using the polynomial method by changing their ordinate values, and the corresponding abscissa values remain unchanged. Thus, the sampling error on y axis only is decreased.

2. **Error mitigation in abscissa coordinates with PSO**
   Sampling data are selected on the fitting curve by using the sampling period of. The early movement of obstacle slightly affects the position prediction. Thus, we set *N=4* and the sampling positions

$$P_n'' = \{p''(t{-}3T_p), p''(t{-}2T_p), p''(t{-}T_p), p''(t)\},$$

$$p'' = \begin{pmatrix} x' \\ y'' \end{pmatrix}$$

   At moment *t*, we regard the ordinate values of $p''(t{-}2T_p)$ and $p''(t{-}T_p)$ as a two-dimensional particle $(x'_{t-T_p}, x'_{t-2T_p})$ and the corresponding y values $(y'_{t-T_p}, y'_{t-2T_p})$ are obtained using the polynomial fitting curve function $y'' = p_n(x'_t)$. The distance between the calculated point $(x'_{t-T_p}, y''_{t-2T_p})$ and the observed position of $p'(t{-}2T_p)$ is denoted as d_{t-1}, and the distance between the calculated point $(x'_{t-2T_p}, y''_{t-2T_p})$ and the observed position of $p'(t{-}T_p)$ is denoted as d_{t-2}.

The fitness function in the PSO model to solve the optimal particle $(x'_{t-T_p}, y''_{t-2T_p})$ is as follows:

$$fit() = \begin{cases} \Delta a(t)^2 & max(\boldsymbol{H}) = 0 \\ max(\boldsymbol{H})^2 & else \end{cases} \tag{12}$$

where $fit()$ means the function of optimization goal and $\Delta a(t)$ is the acceleration jerk at time *t*.

$$\mathbf{H} = \{h_{t-1}, h_{t-2}\}, \tag{13}$$

where

$$h_i = \begin{cases} \dfrac{d_i}{r\_error} & d_i > r\_error \\ 0 & else \end{cases} \tag{14}$$

In Equation (14), $i = t - 1, t - 2$.

Moreover, *H* is a penalty function and reflects the effect of d_{t-1} and d_{t-2}.

From Equations (12)–(14), we can find that the fitness function aims to obtain a minimal amount of change in acceleration $\Delta a(t)$ after the correction of the middle two sampling positions. When the fitting point is within the range of the observation error, the penalty function is set as 0; otherwise, a penalty function that is associated with the above-mentioned differences can be added to the fitness function. Fig. 2 shows that, after the best particle $(x'_{t-T_p}, x'_{t-2T_p})$ is obtained, the optimal $p(t-2T_p)$ and $p(t-T_p)$ are obtained from the polynomial fitting curve function.

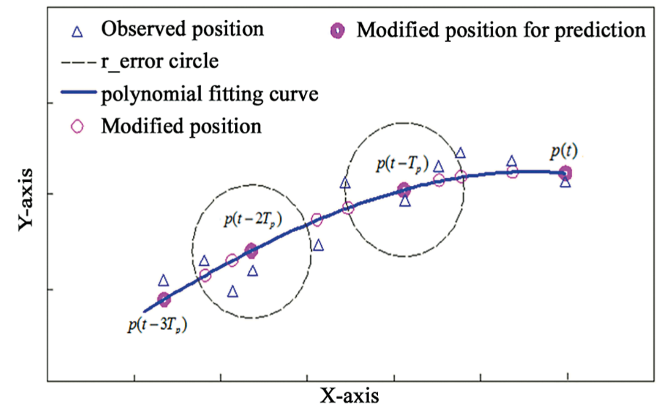


Fig. 2. Error mitigation in x axis with PSO

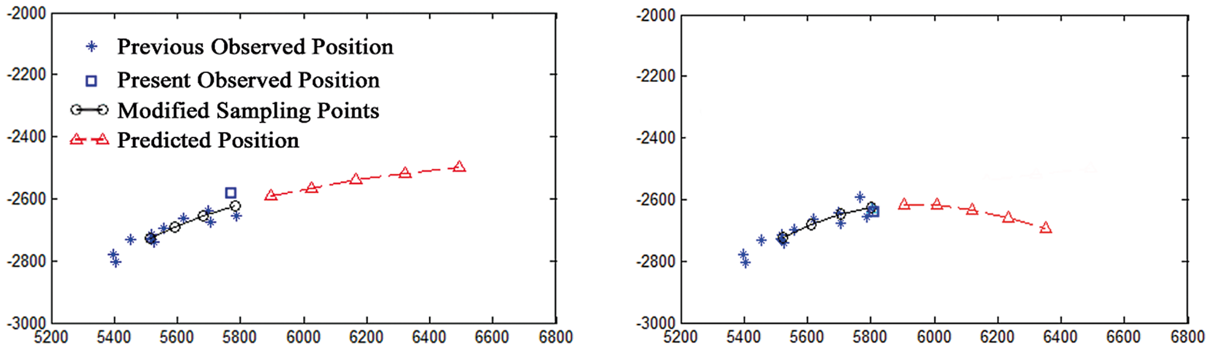
The bidirectioal fitting method shows that, after the error mitigation on both axes, all of the modified trajectory points are within the radar accuracy error range with a high possibility and are within the curve by polynomial fitting. As a result, the change in acceleration is decreased and the prediction accuracy of obstacle position is high.

SIMULATION

We perform two simulations for predicting the trajectory of obstacle during its slow or fast change in movement by using the proposed method. In each simulation, the prediction is processed in two continuous periods. A new observed point appears in the second period. The calculation parameters are set as N=4 and k=5. The symbol meanings are presented in Fig. 3(a).

Figs. 3 and 4 show that, regardless of the slow or fast change in movement of obstacle, both trajectories predicted on the basis of the optimized sampling points maintain motion inertia. The results clearly indicate the moving trend of the obstacle and show the effectiveness of the method in error mitigation.

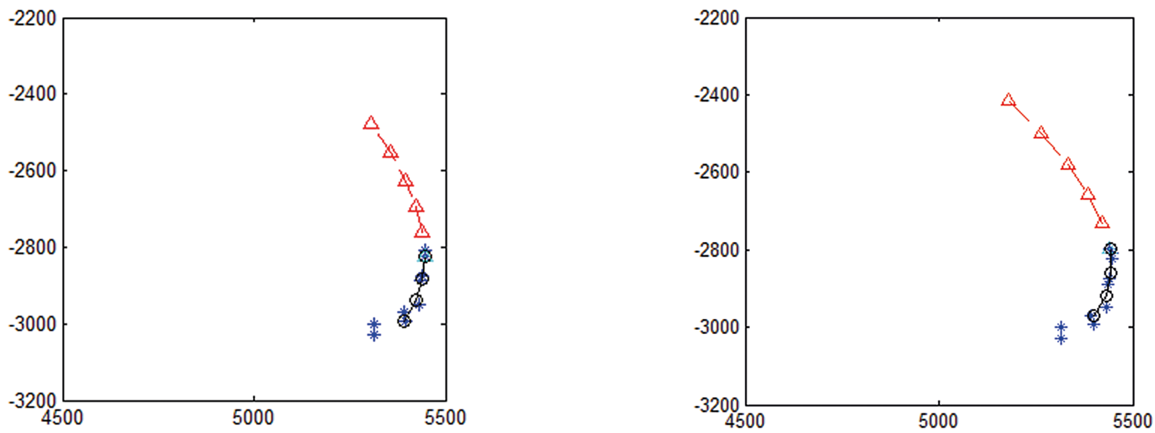
1) Simulation for minor motion change situation



(a) Period 1 *(b) Period 2*

Fig. 3. Trajectory prediction during slow change in movement of obstacle

2) Simulation for major motion change situation



(a) Period 1 *(b) Period 2*

Fig. 4. Trajectory prediction during fast change in movement of obstacle

The prediction is conducted in advance. The errors in prediction are magnified, and the inertia reflected in two periods presents a certain gap. The reason is that the new observed point in the second period provides information that is unavailable in the first period.

3) Simulation of collision avoidance

To test the effect of error mitigation on the avoidance of obstacle, we simulate the collision avoidance of a USV with the Velocity Obstacle (VO) method under MATLAB [23]. In the method, a velocity model between the USV and obstacles is established by the spatial relationship of the position and velocity. The VO method is a collision avoidance algorithm that relies sufficiently on the accuracy of obstacle position and velocity.

In this simulation, the initial position of the USV is (0, 0). The initial position of three obstacles are (1500, –500), (2000, 500), and (6000, –500). The target point is set at (6500, –800). The unit is meter. The obstacles change their speeds and courses randomly. Fig. 5 illustrates the initial headings of four boats. The circles around obstacles indicate the ship domains (the radius of the domain is set to 230 in the simulations), which are used to represent the area of an obstacle that should be avoided.

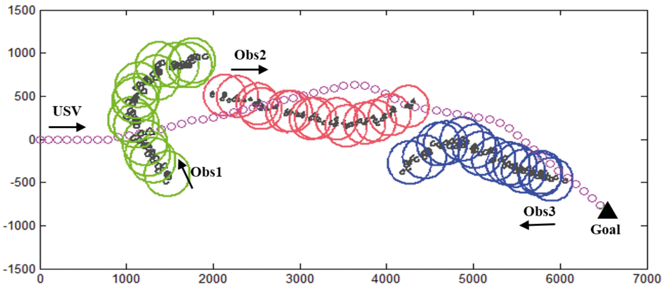


Fig. 5. Simulation of the collision avoidance for unknown dynamic obstacles with error mitigation method

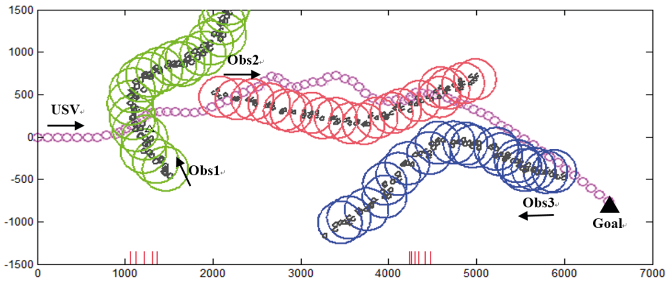


Fig. 6. Simulation of the collision avoidance for unknown dynamic obstacles without error mitigation method

Tab. 2. Correlation data of simulation with and without the error mitigation method

	With the error mitigation method	Without the error mitigation method
Times that the USV enters the domains of obstacles	0	11
Time required to obtain the goal (Unit: period T)	59	85

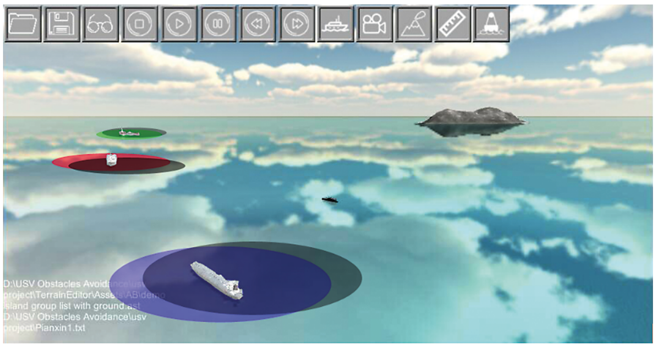


Fig. 7. 3D simulation of the collision avoidance of USV

As shown in Figs. 5 and 6, the observed trajectories of obstacles fluctuate throughout the entire process of collision avoidance, thereby increasing the difficulties in avoidance.

The short red line at the bottom of Fig. 6 shows that, when the USV reaches the abscissa value during the simulation owing to inefficient avoidance, the USV enters into the domain of the obstacle, which is a dangerous situation.

Table 2 shows that no USV enters into the domains of obstacles when the error mitigation method is adopted. By contrast, this situation occurs 11 times when the error mitigation method is not applied, thereby indicating that the avoidance effect is poor.

By comparing the trajectories of the USVs in the two simulations, a frequent fluctuation is observed in the direction and speed of the USV without using the error mitigation method. This finding is due to the unbalanced movement of the obstacles and the existence of observation errors, which may seriously affect the collision avoidance. As shown in Fig. 5, the path of the USV is smooth, because its collision avoidance is based on the modified trajectory of obstacle after error mitigation.

Table 2 also shows the advantage of the error mitigation method in improving collision avoidance efficiency. When using the error mitigation method, the USV takes only 59 cycles to avoid obstacles and reach the goal. On the contrary, the USV without using the error mitigation method requires 85 cycles to complete the same task.

Fig. 7 shows the real-time 3D simulation of collision avoidance with the error mitigation method. In the figure, the obstacle detected is the real position of the obstacle, the gray circle indicates the obstacle domain observed by the radar, and the corresponding colored circle is the obstacle domain after correction. A large deviation exists between the observed and real positions of the obstacle as a result of the existence of radar errors. This deviation may affect the efficiency of collision avoidance of the USV. After adopting the correction algorithm, the domain of the obstacle corresponds to its real position, indicating that the observation errors are effectively eliminated. This simulation can provide a clear insight into the avoidance process of USVs in a real-world environment. The finding indicates the accuracy of the proposed method in predicting obstacle motion.

The trajectory prediction and obstacle avoidance simulations indicate that the bidirectional fitting method substantially eliminates the observation errors of radar and shows the validity and reliability of the proposed method in obstacle avoidance planning.

CONCLUSION

First, we analyze the motion prediction error caused by observation accuracy by using the autoregressive prediction model. Then, an error mitigation algorithm based on polynomial fitting and PSO is proposed to effectively improve the prediction precision. The polynomial method is used to fit the observed path points for eliminating the longitudinal error, and the PSO algorithm is used to correct the fitting points for eliminating the horizontal error of the observed data. The effectiveness of the bidirectional fitting algorithm in error mitigation is verified by trajectory prediction simulations. Moreover, a simulation on collision avoidance is carried out using the proposed method combined with the VO method. The results show the validity and reliability of the algorithm in collision avoidance.

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CONTACT WITH THE AUTHOR

Lifei Song
e-mail: songlifei@whut.edu.cn
School of Transportation
Wuhan University of Technology
Heping Avenue No.1178
430063 Wuhan
CHINA

Zhuo Chen
e-mail: 1304972779@qq.com
Key Laboratory of High Performance Ship Technology
Wuhan University of Technology
Ministry of Education
Heping Avenue No.1178
430063 Wuhan
CHINA

Yunsheng Mao
e-mail: ysmao@163.com
Key Laboratory of High Performance Ship Technology
Wuhan University of Technology
Ministry of Education
Heping Avenue No.1178
430063 Wuhan
CHINA

Zaopeng Dong
e-mail: naval_architecture@163.com
Key Laboratory of High Performance Ship Technology
Wuhan University of Technology
Ministry of Education
Heping Avenue No.1178
430063 Wuhan
CHINA

Zuquan Xiang
e-mail: xiangzuquan@whut.edu.cn
Key Laboratory of High Performance Ship Technology
Wuhan University of Technology
Ministry of Education
Heping Avenue No.1178
430063 Wuhan
CHINA