Research on Technology of Sea Emergency Rescue Based on Unmanned Surface Vehicle

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Abstract. Based on the advantages of small size, easy to carry by large ship, high speed, flexible mobility, no need to drive by human, high autonomy, the Unmanned Surface Vehicle (USV) is very suitable for the sea emergency rescue. During rescue, the USV needs to track the castaway, and it needs to sail to the downstream position of the castaway in the shortest time to release the life-saving equipment. In this paper, the technology of sea emergency rescue of USV is researched, the motion of the castaway is established, and the downstream position and velocity of the castaway is predicted based on Kalman Filter (KF). In addition, the motion model of the USV is established, and the target tracking based on the Dynamic Window Approach (DWA) is carried out, which will guide the USV to reach the rescue position, and local obstacle avoidance is carried out near the castaway to avoid collision. The rescue strategy does not need to consider the influence of the weather on the position of rescue, so it has high adaptability. Finally, the rescue strategy is simulated, the simulation results validate it works effectively.

1. Introduction

When the shipwreck, as time goes on, castaways are more and more scattered due to the influence of sea wind and waves. In order to ensure the safety of the castaways, the shorter the rescue time, the better. The USV has the advantages of small size, fast speed, good mobility and manpower saving, so it is very suitable for the sea rescue task, the rescue research based on USV is also very extensive at home and abroad. Francisco Fernández Ramírez et al. [1] shows a sea rescue system based on a coordinated strategy of an Unmanned Aerial Vehicle (UAV) and a USV. The UAV predicts the position of the castaways with the prediction Artificial Neural Network (ANN), The USV incorporates a Particle Filter (PF) to estimate the castaway location. The paper shows the whole system performance under different situation. Xuesu Xiao et al. [2] research the teams of an USV with an UAV, which will enhance sea casualty incident search and rescue in emergency response phase. This paper proposes compensate for the lack of elevation of the responders by using UAV, thirty autonomous navigation trials in four rescue scenarios prove the successful implementation of a small UAV visually navigating a USV. Ozkan, Mehmet Fatih et al. [3] propose ground map generation and path planning algorithms, in a flooded urban environment, which make use of aerial imaging provided by a UAV. It uses A* [4], GA [5] and PRM [6] path planning algorithms to find near-optimal paths for USV between initial and target position. Finally, Simulations are performed to evaluate the ability of the system algorithms, in flooded urban environments, to find out the most suitable algorithm. In addition, there are also some papers on structural design [7], course control for rescue of USV [8], etc. The lifejacket worn by the castaway is equipped with GPS signal transmitter, which can give position information, but the error is large, and castaway will drift with the current. When search and rescue, the USV has to navigate to the downstream position of the castaway, so it needs to predict the location...
of the castaway in advance, in order to make the USV reach target point before castaway, and release lifesaving equipment from the USV. In this paper, the motion model of castaway and USV is established, the target position of the rescue rafter is predicted based on the KF \cite{9}, and the path planning and local obstacle avoidance are carried out based on DWA \cite{10}. Finally, the simulation experiment is carried out.

2. Position Prediction Rescue Point Based on Kalman Filter

2.1. Motion Model of Castaway

The motion of castaway can be simplified as a uniform linear motion, but the velocity will change slightly. The acceleration can be regarded as a disturbance input with random characteristics. The two-dimensional uniform linear motion model of the target is established as follows:

\[
X(k) = \begin{bmatrix} x(k) \\ \dot{x}(k) \\ y(k) \\ \dot{y}(k) \end{bmatrix}
\]  

(1)

The formula includes the position and speed of the target in the horizontal direction and the position and speed in the longitudinal direction. The system equation of target tracking is shown as follows:

\[
X(k+1) = \Phi X(k) + \Gamma w(k)
\]  

(2)

\[
Z(k) = HX(k) + v(k)
\]  

(3)

where \( \Phi \) is state transition matrix; \( \Gamma \) is noise driving matrix; \( H \) is observation matrix; \( X \) is state vector; \( Z \) is measurement vector.

2.2. Kalman Filter

Kalman filtering was put forward by Kalman in 1960. Once put forward, it has been widely used in various fields. Kalman filter makes use of the dynamic information of the target, tries to eliminate the influence of noise, and obtains an optimal estimation of the target position. This estimation can be the estimation of the current target position, or the estimation of the future position.

State prediction:

\[
\hat{X}(k+1|k) = F(k)\hat{X}(k|k)
\]  

(4)

Covariance prediction:

\[
P(k+1|k) = F(k)P(k|k)F'(k) + Q(k)
\]  

(5)

New interest covariance:

\[
S(k+1) = H(k+1)P(k+1|k)H'(k+1) + R(k+1)
\]  

(6)

Gain:

\[
K(k+1) = P(k+1|k)H'(k+1)S^{-1}(k+1)
\]  

(7)

State update equation:

\[
\hat{X}(k+1|k+1) = \hat{X}(k+1|k) + K(k+1)[Z(k+1) - H(k+1)\hat{X}(k+1|k)]
\]  

(8)

Covariance update equation:

\[
P(k+1|k+1) = [I - K(k+1)H(k+1)]P(k+1|k)[I + K(k+1)H(k+1)]' - K(k+1)R(k+1)K'(k+1)
\]  

(9)

where \( \hat{X}(k+1|k) \) is the k-time prior state estimate, \( \hat{X}(k|k) \), \( \hat{X}(k+1|k+1) \) is the posterior state estimates at \( k \) time and \( k+1 \) time respectively, \( F \) is state transition matrix, \( P(k+1|k) \) is a priori
estimate covariance at k-time, $P(k | k)$, $P(k+1 | k+1)$ is the posterior estimation covariance at k time and k+1 time, $Q$ is covariance of process noise, $K(k+1)$ is Kalman gain, $Z(k+1)$ is measured value, $H(k+1)$ is measurement matrix, $R$ is measurement noise covariance.

3. Point Tracking Based on Dynamic Window Approach

3.1. Motion Model of USV

The dynamic window algorithm considers the motion characteristics of the robot, so it is necessary to establish motion model of USV. Generally, longitudinal motion along the $x_a$ axis and rotational motion around the $z_a$ axis is considered when research USV. As shown in Figure 1.

![Figure 1. USV motion coordinate system](image)

When the USV moves in a straight line, the trajectory in the adjacent time period is a straight line, but when the USV moves in both a straight line and a rotation, the trajectory in the adjacent time period is a small arc. Set the USV's coordinate at time $t$ in some global coordinate system, Set $x(t)$ and $y(t)$ represent the USV's coordinate at time $t$. Set $\nu(t)$ represent the translational velocity of the USV at time $t$, and $\omega(t)$ represent its rotational velocity. The $x(t_n)$ and $y(t_n)$ can be denoted as a function of $x(t_0)$, $\nu(t)$ and $\omega(t)$.

The corresponding equations for the x-coordinate are:

$$x(t_n) = x(t_0) + \sum_{i=0}^{n-1} (F_x^i(t_{i+1}))$$

where

$$F_x^i(t) = \begin{cases} \frac{\nu_i}{\omega_i} (\sin \theta(t_i) - \sin(\theta(t_i) + \omega_i \cdot (t - t_i))), & \omega_i \neq 0 \\ \nu_i \cos(\theta(t_i)) \cdot t, & \omega_i = 0 \end{cases}$$

The corresponding equations for the y-coordinate are:

$$y(t_n) = y(t_0) + \sum_{i=0}^{n-1} (F_y^i(t_{i+1}))$$

where

$$F_y^i(t) = \begin{cases} -\frac{\nu_i}{\omega_i} (\cos \theta(t_i) - \cos(\theta(t_i) + \omega_i \cdot (t - t_i))), & \omega_i \neq 0 \\ \nu_i \sin(\theta(t_i)) \cdot t, & \omega_i = 0 \end{cases}$$
3.2. Dynamic Window Approach
In the two-dimensional space of velocity \((v, \omega)\), there are infinite results, but according to USV’s own limitations and environmental limitations, these velocities can be controlled within the moving range:

\[
v_m = \{v \in [v_{\text{min}}, v_{\text{max}}], \omega \in [\omega_{\text{min}}, \omega_{\text{max}}]\}
\]  

(14)

The USV is limited by its own maximum and minimum speed:

\[
v_{d} = \{(v, \omega) | v \in [v_{\text{c}} - \dot{v}_{\text{d}} \Delta t, v_{\text{c}} + \dot{v}_{\text{d}} \Delta t] \land \omega \in [\omega_{\text{c}} - \dot{\omega}_{\text{d}} \Delta t, \omega_{\text{c}} + \dot{\omega}_{\text{d}} \Delta t]\}
\]  

(15)

In order to stop before encountering obstacles, there is a range of speed under maximum deceleration condition:

\[
v_{a} = \{(v, \omega) | v \leq \sqrt{2 \cdot \text{dist}(v, \omega) \cdot \dot{v}_{\text{a}}} \land \omega \leq \sqrt{2 \cdot \text{dist}(v, \omega) \cdot \dot{\omega}_{\text{a}}}\}
\]  

(16)

The final velocity window is the set of velocities under the above three conditions:

\[
v_f = v_m \cap v_d \cap v_a
\]  

(17)

In the sampling speed group, it is feasible to have more than one group of tracks, so the evaluation function is used for each track. The evaluation function is as follows:

\[
G(v, \omega) = \sigma(\alpha \cdot \text{heading}(v, \omega) + \beta \cdot \text{dist}(v, \omega) + \gamma \cdot \text{velocity}(v, \omega))
\]  

(18)

4. Simulation

4.1. Simulation Flow Chart
Firstly, establish coordinate system and initialize the system, input measurement position data of the castaway into KF, output position and velocity magnitude. Then, get velocity direction using position by least square fitting (LSF) [11], get position of the rescue point by position and direction of castaway, using mean filter (MF) [12] to process velocity magnitude again to reduce error. Finally, the USV tracks rescue point base on DWA. In this simulation, the velocity of castaway is not used in DWA actually, because of velocity of castaway is low. In the future, reciprocal velocity obstacles (RVO) [13]would be considered when using DWA. The simulation flow chart is shown in Figure 2.

4.2. Position Prediction of Rescue Point
The initial position of castaway is \((100,100)\), initial velocity \(v_c = \nu_c = 1 m/s\). Set measurement noise \(\omega = 0.01; 0,0,1\) \cdot \sigma\), process noise \(R = 2 \cdot [1,0,0,1] \cdot \sigma\), \(\sigma\) is gaussian white noise with mean value of zero and variance of 1. Set distance of castaway and rescue point \(L = 20 m\), sampling period \(T = 1s\). As shown in Figure 3.
Figure 3. Position prediction of Rescue Point. (a) Actual Trajectory, Measurement Trajectory, KF Trajectory, Rescue Point Trajectory. (b) Error between Measured Position and Actual Position, Error between KF and Actual Position. (c) Actual velocity Direction, KF Velocity Direction, Error between Them. (d) Actual Velocity Magnitude, KF Velocity Magnitude, Error between Them. (e) Actual Velocity Magnitude, KF and LSF Velocity Direction, Error between Them. (f) Actual Velocity Magnitude, KF and MF Velocity Magnitude, Error between Them.

It can be seen from Figure 3 (a) and Figure 3 (b) that the measured value deviates from the actual value greatly. After KF, the position deviation becomes smaller. It can be seen from Figure 3 (a) that although the predicted position of rescue points has a large deviation, the search and rescue equipment have a relatively long ejection distance, which is far greater than the sum of L and deviation. Figure 3 (c) and Figure 3 (d) show that the velocity direction and magnitude of castaway are inaccurate, the velocity direction is recalculated by LSF, the velocity magnitude is recalculated by MF. It can be seen that the error after processing is small from Figure 3 (e) and Figure 3 (f).

4.3. USV Tracking Rescue Point

Figure 4. Simulation Process. (a), (b) USV Tracking Rescue Point. (c) Distance between USV and Rescue Point. (d) USV Velocity Magnitude. (e) USV Velocity Direction. (f) USV Angular Velocity. The initial position of USV is (0,0), initial direction is 90°. Initial velocity and angular velocity are both 0. Set the radius of castaway (obstacle) 2m. Set USV’s maximum velocity 5m/s, acceleration 0.5m/s², maximum angular velocity 20°/s, angular acceleration 0.5°/s². Set evaluate function parameters $\alpha = 0.08$, $\beta = 0.05$, $\gamma = 0.1$. Set velocity interference $\xi = 0.2 \cdot \sigma$, angular velocity...
interference $\xi_2 = 0.2 \cdot \sigma$. $\sigma$ is the gaussian white noise with mean value of zero and variance of 1. As shown in Figure 4.

Figure 4 (a) shows the whole process of the USV tracks to rescue point from (0, 0) position, it can be seen that USV can realize the application of rescue. Figure (4) (b) shows that USV meets castaway and avoids obstacles. Figure 4 (c) shows the distance change between USV and the rescue point, Figure 4 (d) ~ (f) shows the speed size, speed direction and angular speed of USV changing with time.

5. Conclusion
As is known, there are more and more researches on the technology of USV recently. It is one of the important sea applications to rescue castaways. In this paper, the technology of rescue by USV is studied. The motion model of castaway and USV is established. Kalman filter, LSF and MF are used to get the position and velocity information of castaway, and the position of rescue point is predicted. Based on DWA, the USV can track to the rescue point and avoid obstacles. The simulation results show that the method proposed in this paper is very effective. Next, sea experiment will be carried out to verify feasibility of the research.

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