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Research on AUV positioning and mapping based on improved adaptive Kalman filter

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Abstract: *Aiming at the problem of low positioning accuracy of underwater target, this paper proposes unscented Kalman filter (UKF), which is a common AUV weighted statistical linear regression track tracking algorithm. Its algorithm redundancy is lower than EKF, PF, PSO and other numerical optimization algorithms, and the algorithm efficiency is higher. However, when using UKF filtering algorithm to estimate AUV state variables using UKF, the prediction noise covariance and observation noise covariance are usually set to a certain value, and the AUV motion state is a nonlinear system. With the movement of AUV, the number of iterations of the algorithm increases, which will cause the accumulation of errors, and even lead to the divergence of positioning errors. Therefore, the improved adaptive Kalman filtering algorithm in this paper adds the adaptive adjustment of the process noise covariance matrix Q and observation noise covariance matrix R to the nonlinear filtering system, the aukf filtering can better suppress the decline of filtering accuracy or even divergence, and reduce the cumulative error of the prediction algorithm. Finally, the simulation results show that the target tracking accuracy is effectively improved and the influence of process noise and sensor noise on the prediction process is reduced.*

Keywords: *Autonomous Underwater Vehicle; Aukf algorithm; Improved track prediction accuracy; Adaptive noise covariance matrix*

1. Introduction

In recent years, autonomous underwater vehicle (AUV), as the most widely used automation equipment in marine development, can replace human beings to complete diversified underwater operations in the deep sea with harsh environment and high risk factor, such as marine resource survey, underwater fishing and target tracking [1]. Underwater robot is gradually becoming an important means to assist in the development of seabed resources. The necessary condition for AUV to complete the scheduled task is to obtain accurate position information. Through the research on the design and improvement of aukf track tracking algorithm in AUV control system, the position information of AUV can be better obtained.

At present, the widely used underwater navigation algorithms mainly include the following categories: dead reckoning, inertial navigation, acoustic navigation and geophysical navigation [2]. The position information of AUV is mainly collected by the sensors on the ship to transmit the parameters of the external environment in the form of digital signals to the track tracking module for data processing. At the same time, the state value of the next time is predicted by the state value of the algorithm at the current time, and the control signal of AUV propeller group is generated to control the ship to sail along the desired trajectory.

The difficulty of UKF Algorithm in the application of AUV track tracking is that the waters where the AUV is located are constrained by multiple sets of fluid boundary conditions; The motion state of AUV is mostly nonlinear equations, so it is difficult to obtain reliable linear solutions [3-5]

To solve the above problem, the nonlinear motion equation of AUV is locally linearized by numerical optimization method. Such as; The optimization method of bearings only track tracking based on extended Kalman filter (EKF) algorithm proposed by wangyanyan [6]. The simulation results show that the AUV motion prediction Trajectory Accuracy of this method is high. However, EKF increases the computational redundancy and error value in the transfer process in the process of calculating the state

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of AUV and the Jacobian matrix of measurement, and requires first-order or second-order Taylor expansion in the process of local linearization, which will produce truncation error in the process and affect the accuracy of solving the state vector of AUV. Therefore, allotta proposed an AUV track prediction method based on Unscented unscented Kalman filter (UKF) [7]. The algorithm reduces the computational complexity, but the trajectory prediction error is still large.

Therefore, in order to improve the error accuracy of AUV track tracking algorithm. In this paper, the standard UKF algorithm is improved. In the process of adjusting the prediction noise covariance matrix and the observation noise covariance matrix, the parameters are introduced in the UKF process. By adaptively adjusting the process noise covariance matrix Q and the observation noise covariance matrix R, the filtering accuracy and robustness are improved.

2. AUV modeling

The AUV modeling process mainly analyzes three parts: hull, propeller group and keel. In the process of motion, the external forces mainly include hydrostatic force, fluid lift, fluid resistance, additional mass force, and viscous resistance of propeller group [8-9]. The motion equation of AUV can better characterize the inherent characteristics of AUV in a nonlinear form.

The motion equation of AUV can be approximately expressed as

$$(M_{rb}+M_n)-D(v)v+(C_{rb}+C_n)v+g(\delta)=\tau_G+\tau_p+\tau_F \tag{1}$$

Where M_{rb} represents the mass matrix generated by the characteristics of the rigid body; M_n represents the mass matrix generated by the additional mass force; v is the movement speed of AUV; D is the resistance of the AUV during its movement; C_{rb} represents the Coriolis matrix generated by the characteristics of rigid bodies; C_n represents the Coriolis matrix generated by the added mass force; $g(\delta)$ represents the recovery vector generated during AUV motion; δ is the displacement vector; τ_G represents the external force vector generated by its own mass and buoyancy; τ_p represents the external force vector generated by the propeller group; τ_F represents the external force vector generated by the keel.

In the positioning process of AUV, the three-dimensional positioning can be converted into two-dimensional positioning, and the depth position information can be measured by the depth meter. The horizontal pitch angle changes slightly during movement, and the following motion equation needs to be added

$$X_k=[x_k,y_k,z_k]^T \tag{2}$$

Where, the transformation matrix of the reference coordinate system： x_k,y_k,z_k represents the longitude, latitude and depth during navigation. Through the position information, the transformation matrix of the motion model as the reference coordinate system can be obtained;

$$\begin{cases} x_{k+1}=x_k+V_k\cdot t\cdot cos\varphi_k \\ y_{k+1}=y_k+V_k\cdot sin\varphi_k \\ \varphi_{k+1}=\varphi_k+t\cdot\omega_k \end{cases} \tag{3}$$

Where V_K is the synthesis speed; ω_k is the yaw angular velocity; Heading angle at φ_k position; t is the sampling period. Where V_k and ω_k are input by AUV sensor measurement control system

$$u_k=\begin{bmatrix}V_k\\ \omega_k\end{bmatrix}=\begin{bmatrix}V_{mk}-w_{vk}\\ \omega_{mk}-w_{\omega k}\end{bmatrix} \tag{4}$$

In the above formula, u_k is the control input model; V_{mk} and ω_{mk} are the measured values of the speed and yaw angle of the AUV, w is the Gaussian white noise, $Q_k=\mathrm{diag}[\sigma^2{}_{vk}\quad \sigma^2{}_{\omega k}]$ the covariance matrix of the system process noise. w_k Therefore, the two-dimensional motion equation of AUV can be abbreviated as

$$X_{k+1}=f(X_k,u_k,w_k) \tag{5}$$

Where w_k is process noise.

Through UKF, a corresponding set of discretized AUV state vectors and covariance matrices can be updated at every moment, and then the sigma sampling matrix is used to calculate the mean and covariance weights. The standard UKF algorithm goes through several stages in one cycle, including state prediction, covariance calculation, Kalman gain calculation, state update, and covariance update.

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From research analysis, it can be concluded that compared with traditional algorithms, standard UKF can achieve second-order operational accuracy and achieve ideal trajectory tracking performance. [10-11]

3. Improved AUKF algrithm

3.1. Adptive kalman filter algorithm

Assuming the nonlinear system is as follows

$$x_k = f(x_{k-1} + \varpi_{k-1} \tag{6}$$

$$z_k = h(x_k) + u_k \tag{7}$$

f and h represent the nonlinear functions of the z-system and measurement, respectively. k is the time series, x_k is the state vector, z_k is the observation vector, ϖ_{k-1} and u_k are the process noise and measurement noise, which follow a normal distribution.

When using the UKF filtering algorithm to estimate the AUV state variables, the predicted noise covariance and observed noise covariance are usually set to a certain value. The AUV motion state is a nonlinear system, and as the AUV moves, the number of iterations of the algorithm increases, which will cause error accumulation and even lead to localization error divergence. Therefore, parameters are introduced in the process of adjusting the predicted noise covariance matrix and observed noise covariance matrix using UKF to fully utilize the current data.

I Initialize the state vector and state covariance matrix.

II Time update

Obtain the sampling point x through traceless transformation

$$\chi_{k-1|k-1} = \left[\hat{x}_{k-1|k-1}\hat{x}_{k-1|k-1} + \sqrt{(n+\kappa)P_{k-1|k-1}}\hat{x}_{k-1|k-1} - \sqrt{(n+\kappa)P_{k-1|k-1}}\right] \tag{8}$$

Among them, n is the scaling dimension, k is the scaling dimension, P is the covariance matrix, and $\hat{x}$ is the estimated value of the state vector.

The one-step prediction of the state is:

$$\hat{X}(k/k-1) = A(k-1)\hat{X}(k-1/k-1). \tag{9}$$

The one-step prediction of covariance is:

$$P(k/k-1) = A(k-1)P(k-1/k-1)A(k-1)^T + B(k-1)Q(k-1)B(k-1)^T \tag{10}$$

The Kalman filter gain is:

$$K(k) = P(k/k-1)H(k)^T[H(k)P(k/k-1)H(k)^T + R(k)]^{-1} \tag{11}$$

The status update is:

$$\hat{X}(k/k) = \hat{X}(k/k-1) + K(k)[Y(k) - H(k)\hat{X}(k/k-1)] \tag{12}$$

State covariance update:

$$P(k/k) = [I_n - K(k)H(k)]P(k/k-1) \tag{13}$$

There are defects in the measurement and update process of UKF that affect the filtering accuracy, such as the system filtering error increasing with the increase of system dimension, and the initial filtering value directly affecting the measurement accuracy. Due to the complexity of underwater environments, noise covariance is usually associated with AUV systems, while measuring noise variance is done by sensors. The variance matrix value of measurement noise in underwater systems varies greatly in different environments and is difficult to predict.

Therefore, a residual is constructed based on UKF, which is determined by the observation value at time t and the updated observation mean after UT transformation. This can reduce the difference between prediction and update, and adjust the size with r.

$$E_t = z_t - \bar{Z} - r \tag{14}$$

Introduce the forgetting factor h (0<h<1) and calculate the adjustment parameter d. The mathematical

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parameter r also undergoes dynamic changes over time, which are related to the adjustment parameters and residuals.

The mathematical parameter r also undergoes dynamic changes over time, which are related to the adjustment parameters and residuals.

$$\mathrm{r} = (1 - \mathrm{d}) * \mathrm{r} + \mathrm{d} * (\mathrm{z_t} - \bar{\mathrm{Z}}) \tag{15}$$

Dynamic adjustment of prediction covariance Q and observation covariance R

$$R = (1 - d) * R + d * (E_t * E_t^T - P_{ZZ}) \tag{16}$$

$$Q = (1 - d) * Q + d * [K * (E_t * E_t^T) * K^T + P - F * P * F^T] \tag{17}$$

During the filtering process, when the measurement noise changes, the state of the filter can be determined by β. The smaller the value of β, the more sensitive it is to new information and the stronger its ability to judge changes or anomalies in measurement noise. The maneuverability requirements for underwater carriers are usually low, but drastic changes in attitude can affect the determination of noise statistical characteristics. In a highly dynamic carrier motion environment, maintaining a constant value of β is not conducive to high-precision navigation and positioning of the system. Effective tracking of the measurement noise matrix can be indirectly achieved through the innovation value.

The improved adaptive Kalman filtering algorithm adds adaptive adjustment to the covariance matrix Q of process noise and the covariance matrix R of observation noise. In nonlinear filtering systems, AUKF filtering can effectively suppress the problem of decreased filtering accuracy or even divergence.

$$Q_{k+1} = Q_k + \eta(K_k(\mathbf{z}_k - \hat{\mathbf{z}}_k)(\mathbf{z}_k - \hat{\mathbf{z}}_k)^T K_k^T - Q_k) \tag{18}$$

$$R_{k+1} = R_k + \eta\big((\mathbf{z}_k - \hat{\mathbf{z}}_k)(\mathbf{z}_k - \hat{\mathbf{z}}_k)^T - R_k\big) \tag{19}$$

Where η is the step size for adjusting the coefficient to control noise.

The dynamic model generates errors during the simulation process, which affect the navigation accuracy. Introducing adaptive factors can further suppress the deviation of initial values and the imbalance of model parameter matching. The AUKF algorithm can further improve the accuracy of navigation through adaptive factors based on UKF, so the principle of adaptive estimation is applied to AUV when the system model is in an abnormal state.

The improved adaptive Kalman filter has the following advantages, including: enhanced robustness: by dynamically adjusting the noise covariance, the filter can better adapt to different noise conditions, improved accuracy: in dynamic environments, it can maintain high state estimation accuracy, especially in cases of severe noise changes, with wide applicability: suitable for various nonlinear dynamic systems, especially in practical applications with good performance.

4. Simulation

4.1. Parameter design in simulation

In order to verify the progressiveness and effectiveness of the AUKF algorithm, the standard UKF algorithm and the adaptive UKF tracking algorithm were simulated on the AUV SLAM model through MATLAB, and the obtained track prediction results were added to the algorithm the adaptive adjustment of the process noise covariance matrix Q and the observation noise covariance matrix R in the nonlinear filtering system. Several different AUV motion tracks were designed in the two-dimensional plane. The EKF algorithm prediction track, the UKF algorithm prediction track, the AUKF algorithm prediction track, and the BDS real motion track were simulated using MATLAB to compare error values. The performance of the improved algorithm was verified through simulation experiments.

This is shown in Figures 1 and 3, assuming the target is moving in two-dimensional space, the initial position (x, y) of target 1 is (2,0), and the velocity environment is in a rectangle of 200m × 200m. The initial velocity of the AUV during motion is set to 0.97m/s, the velocity noise is 0.02m/s, the time interval for control signal transmission is 0.036s, and the maximum observable distance is set to 60m through sonar parameter indicators. The influence of sampling interval on model design is considered, and the state model is divided into two parts: sampling interval correlation term and sampling interval independent term, which are verified through debugging.

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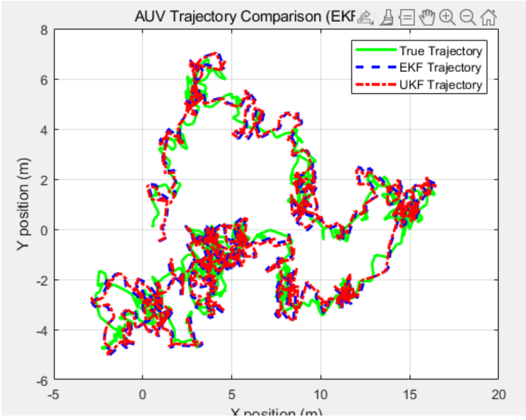

Figure 1: EKF and UKF simulation trajectories and predicted trajectories

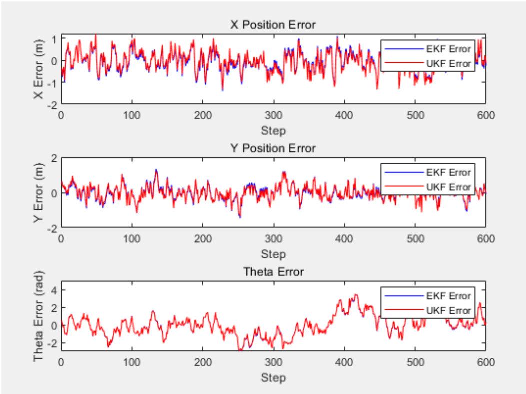

Figure 2: Estimation error of UKF initial positionF

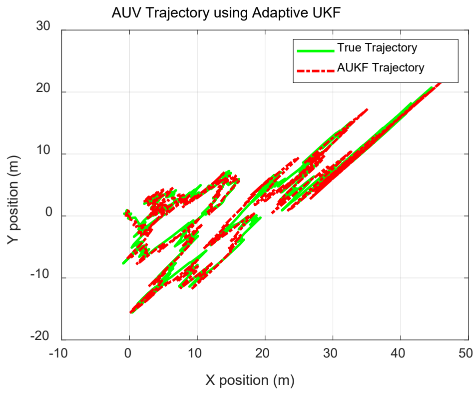

Figure 3: AUKF simulation trajectory and predicted trajectory

Figure 4: Error estimation of AUKF initial position

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By comparing the experimental results through simulation, the tracking error waveforms of the two trajectories in Fig. 2 and Fig. 4 are obtained, it can be seen that the standard UKF prediction curve has a good fit with the tracking trajectory in the first half of the curve, but the deviation of the predicted trajectory in the second half of the curve becomes larger and the tracking effect is average. Moreover, the prediction curve tends to gradually diverge, mainly due to the algorithm's accumulated error caused by noise; This is related to the accumulation of algorithm errors and the adaptability of the algorithm itself; The tracking performance of the adaptive UKF algorithm has relatively improved; The overall tracking performance of the AUKF algorithm curve is relatively stable, with low variance in the first half of the curve and large deviation in the second half of the predicted trajectory curve; The overall average tracking error of the AUKF algorithm is slightly lower than that of the standard UKF algorithm, and its path fit is also relatively ideal. Based on the simulation results of trajectory tracking, it can be found that the adaptive UKF algorithm can accurately track the true expected trajectory of AUVs. Compared with the standard UKF algorithm, the AUKF tracking curve is more stable and smooth, with stronger adaptability, which is consistent with previous theoretical expectations. The prediction error has also remained within an acceptable range

The purpose of the adaptive UKF algorithm is to reduce the impact of accumulated errors on the tracking results during the AUV trajectory tracking process. Therefore, the trajectory is plotted using x_true_hist and the trajectory histories x_ekf_hist, x_ukf_hist, and x_aukf_ist of each filter. The figure compares the real trajectory with the trajectories estimated by three different filters

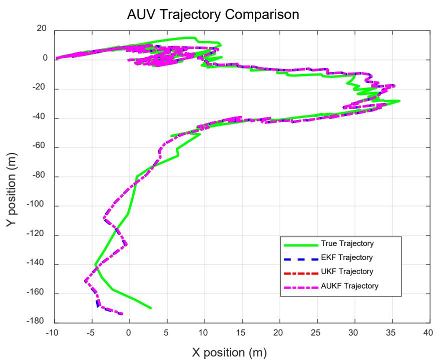

Figure 5: Comparison of x_ekf_histt trajectories

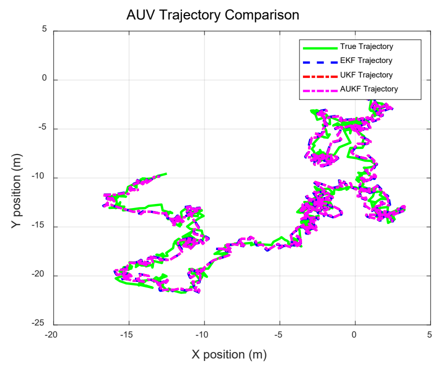

Figure 6: Comparison of x_ukf_hist trajectories

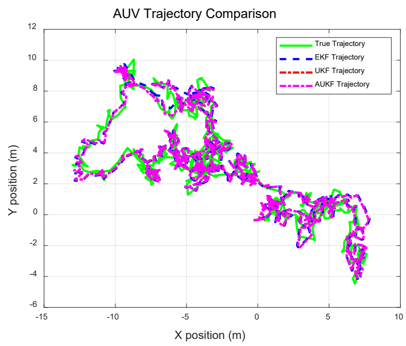

Figure 7: Comparison of x_aukf_hist trajectories

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Comparing the fluctuation amplitudes of the three trajectory curves, it can be seen that the average error of the AUKF algorithm is smaller than that of the UKF algorithm in both speed and attitude, indicating that the filtering accuracy of the former is higher than that of the latter, Fig. 5, Fig. 6, and Fig. 7 are trajectory tracking diagrams under three filters, respectively.

5. Conclusion

An adaptive unscented Kalman filter algorithm based on AUV track tracking technology is proposed. When using UKF filtering algorithm to estimate AUV state variables using UKF, the prediction noise covariance and observation noise covariance are usually set to a certain value, and the AUV motion state is a nonlinear system. With the movement of AUV, the number of iterations of the algorithm increases, which will cause the accumulation of errors, and even lead to the divergence of positioning errors. Therefore, the improved adaptive Kalman filtering algorithm in this paper adds the adaptive adjustment of the process noise covariance matrix Q and the observation noise covariance matrix R to the nonlinear filtering system, and adds three different noise filters at the same time. It is found that the tracking curve of the improved algorithm is smoother and more consistent, indicating that the cumulative error caused by noise can be effectively reduced and the noise resistance is high under track tracking, which basically meets the expected requirements.B.

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