Application of Kalman Filter in Ship Track Prediction

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Abstract

With the development of computer control technology, in the field of ship track prediction, people have developed various intelligent algorithms to ensure the safety of ship navigation. In this paper, the ship track prediction technology based on Kalman filter algorithm is proposed, and the appropriate model is established. Then the simulation performance is verified by simulation experiments.

Keywords

Ship track, Motion prediction, Kalman filter.

1. Introduction

The ship tracking prediction includes the position of the ship, the speed of the navigation and the acceleration. The Kalman algorithm has obvious advantages in the processing of motion information, and can effectively overcome the influence of nonlinear interference and strengthen the motion. The predictive ability of behavior. Although the Kalman filter has a long calculation time compared with other tracking methods, the tracking prediction of the ship is a nonlinear process, which requires a comprehensive consideration of the relationship between accuracy and calculation time to achieve tracking accuracy. This paper focuses on the application of this algorithm in track prediction[1].

2. Kalman filter algorithm

Kalman filtering only needs to obtain the current value of the target through the previous estimate and the most recent observation data. It is used to estimate the state of the linear system. It can use the measured value to estimate the state of the modified estimate and provide a reliable state estimation. Its estimate is controlled by a recursive feedback form. Kalman filter has two types of algorithms: continuous and discrete. The continuous type needs to be discretized first. The discrete algorithm can be directly implemented on a digital computer. The discrete type is mainly discussed here[2].

2.1 System model

Kalman filtering introduces state space theory into the mathematical modeling process of physical systems, which assumes that the system state can be represented by a vector $X \in R^n$ of n-dimensional space. State random difference equation of the system:

$$X_k = AX_{k-1} + BU_k + W_k \tag{1}$$

the measurement equation is:

$$Z_k = HX_k + V_k \tag{2}$$

A, B, H are state transformation matrices, here assumed to be constant, X_k is the system state variable, U_k is the system control input, Z_k is the observed variable, $Z_k \in R^m$, P_k is the covariance matrix, and W_k is the system process stimulus Noise, obeying the white noise of normal distribution, ie $W_k \sim N(0, Q)$, Q is the process noise covariance matrix, V_k is the observed noise, obeys the white noise of normal distribution, ie $V_k \sim N(0, R)$, R is the observed noise covariance matrix, and W_k, V_k are independent of each other.

2.2 Calculation prototype

Starting from the established system model, the computational prototype is derived. The symbol _ is used to represent the prior, and the ^ is the estimate. The state before the kth step is known to estimate the kth step as the a priori estimate, and the observed variable Z_k is known to estimate the kth step as the posterior estimate. A priori estimation error:

$$E_k^- = X_k - \hat{X}_k^- \tag{3}$$

the covariance matrix of the prior estimate:

$$P_k^- = E(E_k^- E_k^{-T}) \tag{4}$$

a posteriori estimation error:

$$E_k = X_k - \hat{X}_k \tag{5}$$

the covariance matrix of the posterior estimate:

$$P_k = E(E_k {E_k}^T) \tag{6}$$

2.3 Motion prediction

The predicted position cannot be calculated before the desired measurement is obtained, and a recursive algorithm can be used to solve the problem of how to predict the next position of the ship. The initial value $y(t)$ is obtained to predict the next time $y(t+1)$, and after the prediction is completed, the true position of the ship at time $(t+1)$ is measured. Thus $y(t+1)$ is changed to the initial value, and the position at time $(t+2)$ is predicted by $y(t+1)$. After such recursive iterations, until the prediction and correction of the ship's track is completed, this is the idea that Kalman filter predicts the ship's track[3].

2.4 Kalman filter modeling

Kalman filtering mainly consists of two processes: estimation and correction. The estimation process mainly uses the time update equation to establish an a priori estimate of the current state, and forwards the current state variable and the error covariance estimate value in time to construct a priori estimate for the next time state. The calibration process is responsible for feedback, using the measurement update equation to establish an improved posterior estimate of the current state based on the a priori estimate of the estimation process and the current measured variable[4,5].

In the time update phase, it is mainly based on the state of the current phase to predict the state of the next time period and the prediction of the error covariance of the next phase[6].

Time update equation:

$$\hat{X}_k^- = A\hat{X}_{k-1} + B\hat{U}_{k-1} \tag{7}$$

$$P_k^- = AP_{k-1}A^T + Q \tag{8}$$

A, B are state transformation matrices, here assumed to be constant, X_k is the system state variable, U_k is the system control input, P_k is the covariance matrix, and Q is the process noise covariance matrix.

The measurement update phase is to correct the prediction made during the time update phase, and to improve the prediction accuracy by comparing the difference between the real value and the predicted value to reduce the error. Measurement update equation:

$$K_k = P_k^- H^T (HP_k^- H^T + R)^{-1} \tag{9}$$

$$\hat{X}_k = \hat{X}_k^- + K_k(Z_k - H\hat{X}_k^-) \tag{10}$$

$$P_k = (I - K_k H)P_k^- \tag{11}$$

H is the state transformation matrix, which is assumed to be a constant, P_k is the covariance matrix, R is the observed noise covariance matrix, X_k is the system state variable, Z_k is the observed variable, I is the unit matrix, $Z_k - \hat{X}_k^-$ reflects The degree of inconsistency between the predicted value and the actual value becomes a residual of the measurement process, and K is the residual gain, where K_k is a way of obtaining it.The algorithm flow chart can be represented by the following figure.

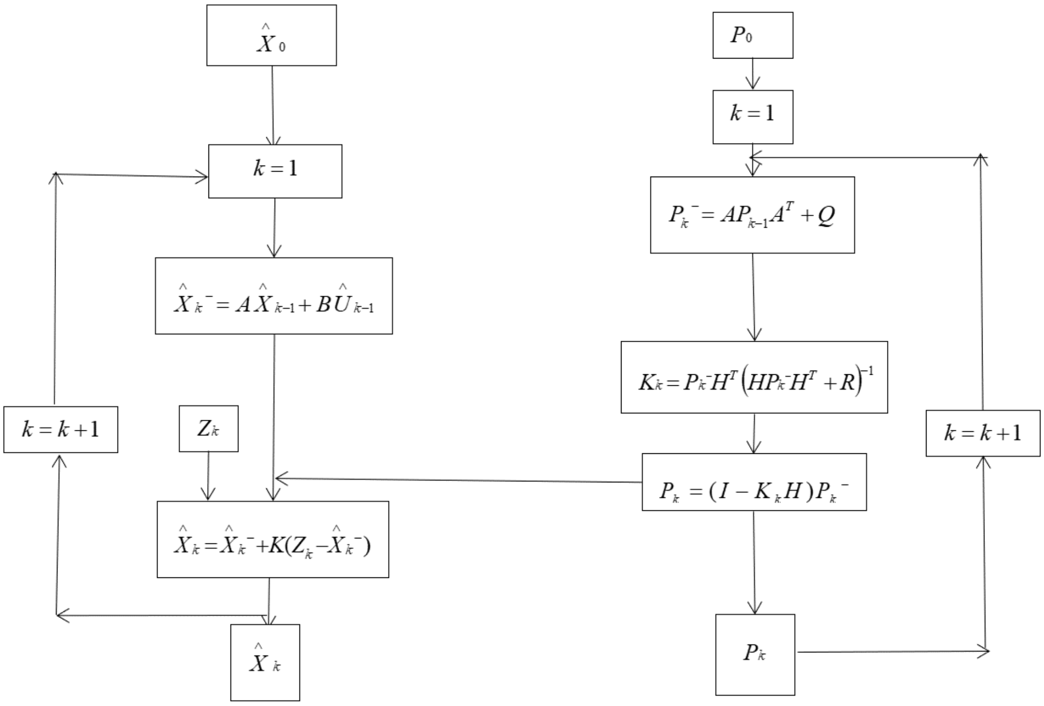

Figure 1 Basic flow of Kalman filtering

In a filtering cycle, from the order of Kalman filtering in using system information and measurement information, Kalman filtering has two obvious information update processes: time update process and measurement update process. Equation (7) illustrates a method of estimating a state estimate at time k from the state at time $k-1$, and equation (8) quantitatively describes the quality of such prediction. In the calculation of these two equations, only the information related to the dynamic characteristics of the system is used. From the time-lapse process, the two equations advance the time from $k-1$ to k, so the two equations describe the Kalman filter. Time update process. The remaining formulas are used to calculate the correction amount for the time update value, which is determined by the quality of the time update P_k, the quality of the measurement information R_k, the observation model matrix H_k, and the specific measurement value Z_k. All of these equations revolve around one purpose, namely the correct and reasonable use of the measurement Z_k, so this process describes the measurement update process of the Kalman filter[7].

3. Simulation Results

3.1 Initialize kalman filter parameters

Based on the above theoretical knowledge, after determining and initializing different parameters, a Kalman filter model can be established for tracking. The sampling interval is set to $1s$, and the simulation time is 181 s. Looking at the previous formula, there are five parameters A, B, H, Q and R that need to be determined. Where state transformation matrix $A = I_{6\times6}$, $B = I_{6\times6}$, H is initialized to:

$$H = \begin{vmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{vmatrix}$$

The process noise covariance matrix $Q = I_{6\times6}$, the observed noise covariance matrix $R = 0.01 \times I_{3\times3}$, and $I_{N\times N}$ represents the unit matrix of $N \times N$.

After all the parameters have been initialized, applying the above formula, a model of the Kalman filter can be established to simulate the tracking of the ship's track.

3.2 Results test

The simulation experiment was carried out based on the actual measured data of a ship's motion. Some of the data is shown in the following table.

Table 1 Partial measured data

Longitude	Latitude	Datatime
122.733284	29.822222	2017/3/15 1:48:46
122.733276	29.822788	2017/3/15 1:48:47
122.733276	29.823242	2017/3/15 1:48:48
122.733276	29.823708	2017/3/15 1:48:49
122.733276	29.824163	2017/3/15 1:48:50
122.733276	29.824625	2017/3/15 1:48:51
122.733276	29.825081	2017/3/15 1:48:52
122.733276	29.825542	2017/3/15 1:48:53
122.733284	29.825994	2017/3/15 1:48:54

According to the above algorithm, the simulation is performed in the Matlab R2018b environment, and the following figure is the simulation result.

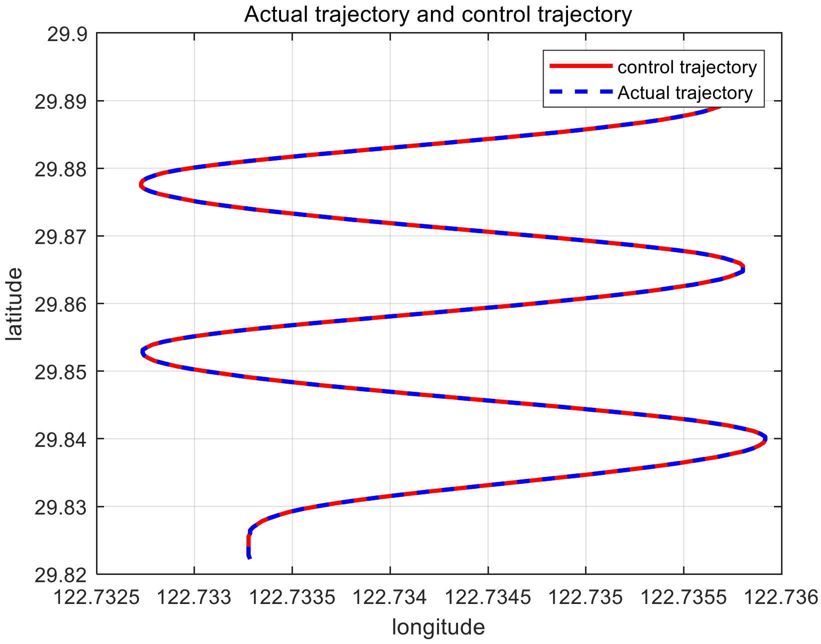

Figure 2 Actual trajectory and predicted trajectory

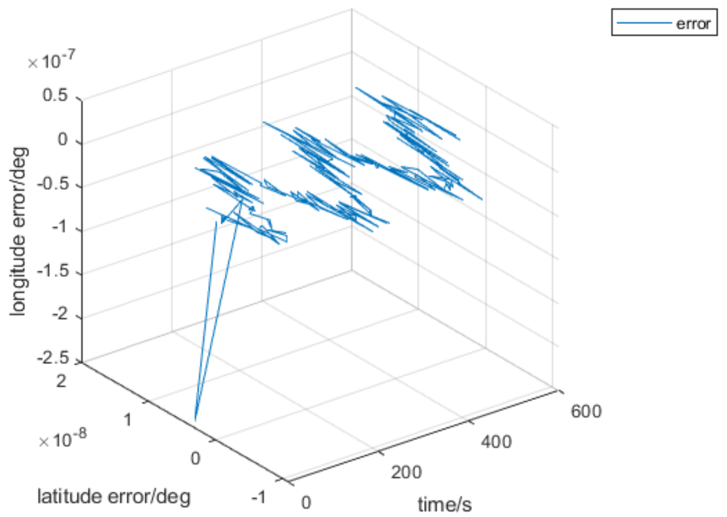

Figure 3 Estimation error

When the current target is in a uniform motion state or when the maneuver strength is low, it can be seen from the graph that the prediction and the actual movement are very matched. However, it is not enough to analyze the trajectory of the ship. It is also necessary to analyze the error of each movement moment to test the prediction accuracy.

As can be seen from the above figure, the error is very small, and the estimation effect is good. However, in this simulation, the process noise covariance matrix Q and the observed noise covariance matrix R are assumed to be constant values. However, in practice, both Q and R will dynamically change with the motion of the research object, and R is mainly determined by the measuring instrument itself. And Q is uncertain. Especially when the target motion situation becomes complicated, the time-varying Q has a great influence on the tracking effect when the target-to-ground heading and the speed change are large. In the traditional Kalman filter, it is usually assumed that Q is fixed and reduced. The tracking accuracy is not obvious when the uniform motion state or the maneuvering strength is low[8].

4. Conclusion

In this paper, the track tracking of the ship is studied. The Kalman filter is used to predict the future position of the tracking point, and the tracking is completed in a short time. From the above simulation results, the result is reasonable, and the other is The error analysis of longitude and latitude shows that these errors are within the allowable range. It can be seen that Kalman filtering has broad application prospects in tracking devices.

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