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A Kalman Filter Model for Ship Navigation Accuracy Optimization

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Abstract. Aiming at the problem of improving the navigation accuracy of ships, a Kalman filter algorithm based on optimization is proposed for navigation optimization. On the basis of studying the dead reckoning knowledge, we establish the dimensional dynamic equation of the ship integrated navigation system. Then the extended Kalman filter is adjusted by using fuzzy logic adaptive controller (FLAC) and it is applied to GPS/INS information fusion to enable it to have adaptive ability to deal with environment disturbance. Finally, the method is used to simulate the GPS/INS integrated navigation system on MATLAB platform. The results show that the improved model can effectively use part of the system data to update and iterate, and improve the stability and reliability of the filter, so it is also better suitable for ship navigation and target tracking.

Keywords. Kalman filter; FLAC; ship navigation; GPS/INS; fuzzy control

1. Introduction

The integrated navigation system is to organically combine the single navigation equipment with the help of computers under the conditions of existing equipment, and achieve the purpose of improving the positioning accuracy of ships through the comprehensive processing of navigation information. The key to improve the accuracy of the system through the combination of navigation information is to comprehensively process the navigation information of each subsystem [1]. Kalman filter is an ideal integrated navigation data processing method. For a long time, extended Kalman filter (EKF) has become the most widely used nonlinear estimation method because of its simple method, easy implementation, fast convergence and other advantages. When encountering strong nonlinear problems, or Jacobian matrix and Hessians matrix are not available, EKF method will fail Moreover, EKF needs derivation, so we must clearly understand the specific form of nonlinear function, and cannot do black box packaging, so it is difficult to apply modularity. At present, although there are many improved methods for EKF, such as Gaussian truncation EKF iteration EKF, some defects are still difficult to overcome [2].

In this paper, a fuzzy controller is added to the classical Kalman filter. The rules of the fuzzy controller are based on expert knowledge or the long-term experience of manual operators. In the experiment of estimating GPS/INS integrated navigation system, the optimization and adjustment method of fuzzy controller parameters is proposed. Firstly, the research status of ship positioning and navigation and track prediction is analyzed, and the dynamic model and measurement model of ship integrated navigation system are established. Then, according to the changes of ship

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positioning and navigation and track, the fusion algorithm is used to fuse the collected navigation data. Finally, the design method of integrated Kalman filter is given, and the number of copies of the algorithm is analyzed on the MATLAB platform. The results show that the predicted trajectory and the actual positioning error of propagation of this scheme are very small, and it is superior to the classical Kalman algorithm in the comprehensive ability of positioning navigation and trajectory prediction.

2. Principle of Dead Reckoning System

2.1 Establishment of Ship Tracking Target Model

Target tracking is a part of radar data processing. The basis of data processing is estimation theory, which requires the establishment of a system model to describe the dynamic characteristics of the target and the measurement process [3]. The system model is generally divided into state equation and observation equation. The state equation mainly reveals the motion law of dynamic targets; There are two kinds of observation equations: linear and nonlinear. For nonlinear cases, they can be expressed by linearization. Only linear equations are considered. The state equation and measurement equation of the target are:

$$\begin{cases} X(k+1) = \Phi(k)X(k) + W(k) \\ Z(k+1) = H(k+1)X(k+1) + V(k) \end{cases} \tag{1}$$

The statistical characteristics of process and measurement noise are

$$\begin{cases} E(W(k)) = q = 0 \\ E(v(k)) = r = 0 \\ E(W(k)V(j)^T) = 0 \\ E(W(k)W(j)^T) = Q\delta_{kj} \\ E(v(k)v(j)^T) = R\delta_{kj} \end{cases} \tag{2}$$

where k is time, $\Phi(k)$ is state state translation matrix, $X(k)$ is the object stata vector to be estimated, $W(k)$ is the white Gauss process noise sequcnce with 0 mean whose covariance is $Q(k)$ and $Z(k)$, $v(k)$ is is the white Gauss measuring noise sequence whose covariance is R_k, δ_{kj} is Kronecker function, $W(k)$ and $v(k)$ are uncorrelated zero mean white noise sequence.

2.2 Integrated Navigation System

At present, the most commonly used integrated navigation system is the integrated navigation system of GPS and inertial navigation system, referred to as GPS/INS integrated navigation system, GPS and dead reckoning integrated navigation system, referred to as GPS/DR integrated navigation system. However, due to the high price of inertial navigation equipment, its application is limited. In recent years, there have been many literatures on the fusion methods of GPS and ins. There are usually two methods of using EKF to fuse the data from GPS and ins. One is to compare the pre-processed

GPS data and INS data respectively, and upgrade the ins filter with its deviation [4-8]. The other is to first compare the observation output of GPS and INS, and then correct the observation value of INS after filter processing, as shown in figure 1.

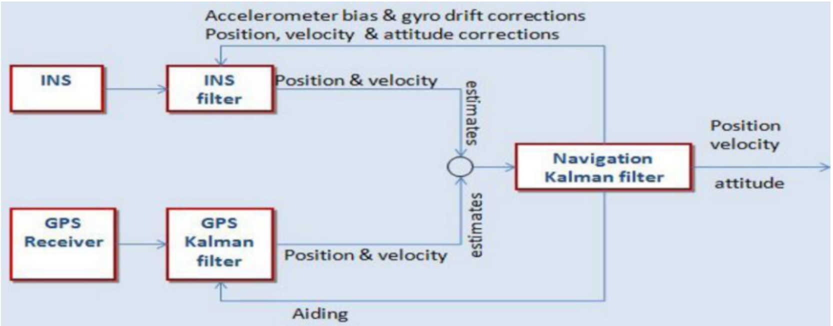

Figure 1. Filter based on integration of INS and GPS.

The system dynamic model and measurement model of CPS and ins are nonlinear, so EKF is needed. In reality, when the state parameters of the system are constantly subject to uncertain interference or the complex system dynamic model is described as a relatively simple mathematical model, the filtering process is prone to divergence. In order to prevent divergence during filtering, it is necessary to make the filter have adaptive function.

3. AIS Trusted Demand Evolution Propagation Model Based on Big Data

3.1 Data Fusion

The key research content of this system is to make it work more reliably in the situation of poor reception of positioning satellite signals through information fusion. In GPS/INS integrated navigation system, Kalman filter is used to estimate various states of the system. In the process of sensor data fusion, each sensor will have errors and obey Gaussian distribution. First of all, the data measured by each sensor may be inconsistent, such as the longitude and latitude obtained by GPS, the acceleration obtained by IMU, etc., so its data format needs to be consistent now. Covariance also represents the relationship between the measured value and the mean (true value), so the smaller the covariance, the higher the degree of its reliability. Therefore, it is necessary to weigh the prediction state obtained by these two ways, and calculate the weight of the fusion of the two through covariance, that is, Kalman gain KG [9]. The specific calculation steps of this process are described as follows:

The observation model in time updating phase includes the position parameter x_i and y_i output by INS, radar altimeter height Z_R and INS information Ψ_t, φ_t, θ_t, that is

$$Z_k^{time\,measuring} = [x_l \ \mathrm{y}_l \ Z_R \ \Psi_t \ \varphi_t \ \theta_t] \tag{3}$$

The transition matrix at time updatinh phase is

$$A_k^{time\ \text{updating}} = \begin{bmatrix} I_3 & 0_3 & \Delta I_3 & 0_3 \\ 0_3 & I_3 & 0_3 & \Delta t_1 I_3 \\ 0_3 & 0_3 & I_3 & 0_3 \\ 0_3 & 0_3 & 0_3 & I_3 \end{bmatrix} \quad (4)$$

The observation matrix at time updating phase is

$$H_k^{time\ \text{updating}} = \begin{bmatrix} I_3 & 0_3 & 0_3 & 0_3 \\ 0_3 & I_3 & 0_3 & 0_3 \end{bmatrix} \quad (5)$$

The observation model at measuring updating phase is the output pose parameters in vision based pose estimation as

$$Z_k^{measuring\,updating} = [x_v\ \ \mathrm{y}_v\ \ z_v\ \ \Psi_v\ \ \varphi_v\ \ \theta_v]^T \quad (6)$$

The transition matrix at measuring phase is

$$A_k^{measuring\,updating} = \begin{bmatrix} I_3 & 0_3 & \Delta t_2 I_3 & 0_3 \\ 0_3 & I_3 & 0_3 & \Delta t 2 I_3 \\ 0_3 & 0_3 & I_3 & 0_3 \\ 0_3 & 0_3 & 0_3 & I_3 \end{bmatrix} \quad (7)$$

The observation matrix at measuring updating phase is

$$H_k^{measuring\,updating} = \begin{bmatrix} I_3 & 0_3 & 0_3 & 0_3 \\ 0_3 & I_3 & 0_3 & 0_3 \end{bmatrix} \quad (8)$$

3.2 Kalman Filter Based on Fuzzy Control

In practical application, we often obtain one observation discretely, such as radar observation of aircraft trajectory, sensor capture of a physical quantity change of the measured object. The structure of INS/GPS Integrated Navigation System Based on fuzzy control Kalman filtering is shown in figure 2: Using MATLAB to create a fuzzy reasoning system which is a method used in many places and can well simulate people's understanding and judgment of uncertain things, especially in the aspect of simulating people's understanding and decision-making, and it can be expressed very succinctly [10]. FIS obtains the measurement noise adjustment factor according to the fuzzy rules and adjusts the optimal state of Kalman filter [11].

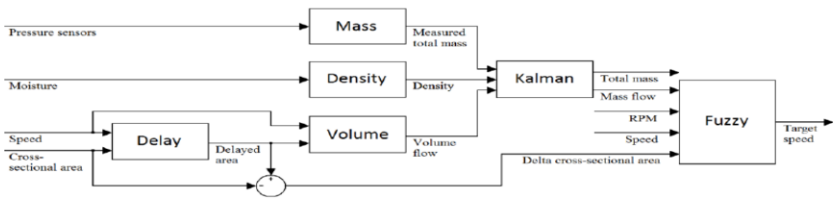

Figure 2. The structure of fuzzy control Kalman filtering

This paper chooses the variance of residuals p and r as two input of FLAC. Considering the residuals maybe multi-dimension, only the first value is adopted and the output of FLAC is a. Then the variance of residuals and mean are fuzzifd and the membership function of them are “trimfs”, which denote three fuzzy sets. When the variance of residuals and mean lie in three dirrerent fuzzy set, the output is related to the input value, according to the judgement of the output change of fuzzy adaptive system according to the characteristics of Kalman filter. The variance and mean can be acquired based on the monitoring residual of certain sample point. is determined by fuzzy logic to keep the residual as white noise with zero mean, whose membership functions are depicted in figure 3 and the control rule is listed in table 1.

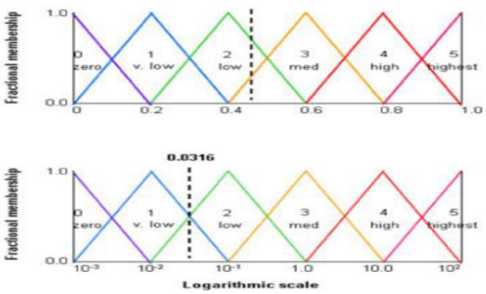

Figure 3. The structure of fuzzy control Kalman filtering

Table 1. fuzzy controller rule table

u_{de}	u_e			
	Z	S	M	B
N	Z	Z	F	S
Z	Z	S	M	F
P	M	M	S	F

4. Simulations

In order to realize the simulation of ship target, the traditional Kalman algorithm is compared with the algorithm in this paper All simulation implementations are carried out in the same software and hardware environment. The CPU is Intel (R) core (TM) 2 Q8400, the memory is 16GB, and the operating system is Cenotos 7.3, which is implemented under the MATLAB R2017b simulation platform. Suppose the ship moves in a straight line at a constant speed, the initial position of the target (U0, Y0) = (45km, 60km), course φ= 30 °, the simulation time of target speed is 500s, and the radar sampling period is t=1s; The planned speed is 30 knots The planned course is 60 degrees Heading noise power spectral density 0.000196 (rad/s).

The federal filter designed in this paper is simulated. In the test, the fusion period and local filtering period are set to be 1 s. Figure 4 and Figure 5 show the comparison of GPS longitude and latitude data before and after filtering: the dotted line curve in the figure is unfiltered GPS data, and there are burrs and mutations in many places on the dotted line curve Burr data means that the speed is not zero, but the duration is not more than 4S. Generally, the speed of such data is not very large, which belongs to burr data caused by measurement error. Such data usually occurs in the idle period Solid curve is the filtered data First, preprocess the trajectory data. From the results of these fugures, it can be seen that within an observation period, ephemeris error belongs to systematic error, which is a kind of starting data error. It not only seriously affects the accuracy of single point positioning, but also an important error source of precision relative positioning, which will effectively reduce the impact of large GPS data errors on track tracking.

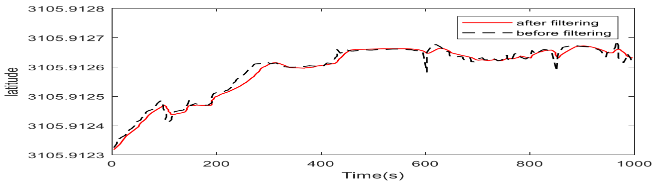

Figure 4. GPS latitude data change before and after Kalman filter.

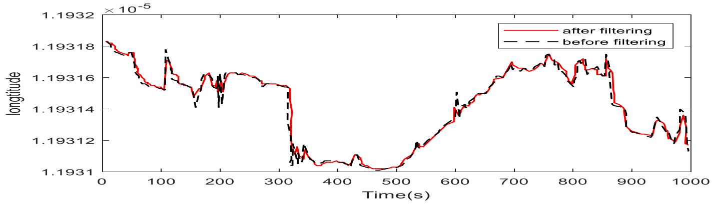

Figure 5. GPS longitude data change before and after Kalman filter

The simulation results of position error are shown in table 2. In gps/ins integrated navigation, the error state is the difference between ins state and auxiliary source state (GPS). The route of the ship is planned in advance. For INS/GPS integrated navigation system, the output of INS is usually regarded as the standard trajectory. The position error increases with the growth of simulation time, which far exceeds the requirements of standard trajectory positioning accuracy, resulting in the decline of the stability of the integrated navigation system. If the navigation system is not updated as an independent INS, we expect the long-term error to increase significantly. After Kalman filtering, the data information of each subsystem is well integrated, and the position error of the navigation system output is greatly reduced, which improves the navigation longitude of the navigation system.

Table 2. Standard deviation of navigation accuracy

Status	Easterly error		Westly error		Southly error		Northly error	
Time(s)	CKF	FAKF	CKF	FAKF	CKF	FAKF	CKF	FAKF
1-900	0.0039	0.0205	0.0204	0.0105	0.1552	0.0136	0.1264	0.2547
901-1800	0.1652	0.0781	0.0609	0.0185	0.8383	0.5536	1.3589	0.2701
1801-2700	0.1183	0.0114	0.0617	0.0349	0.5638	0.3217	0.4868	0.1105
2701-3600	0.0011	0.0112	0.0138	0.0118	0.2740	0.1599	0.4231	0.1986

From the above analysis, it can be seen that within the initial 900s, the error of conventional Kalman filter and fuzzy adaptive Kalman filter is basically the same, and the performance difference is small. After 2700s, the fuzzy filter system has high controllability and fast response, which can compensate each harmonic, suppress flicker and compensate reactive power. Therefore, under the same conditions, the estimation ability is relatively stable, reflecting high accuracy and anti-interference. In the next step, we will put more emphasis on the ability of the filter to maintain the edge texture information and resolution. By adaptively adjusting the amplification filter through innovation calculation, we can consider carrying out an additional measurement of a specific order of magnitude, eliminate the data errors caused by noise or accidental interference, and weaken its impact on the filtered value.

5. Conclusion and Future Work

Classical Kalman filtering can also be regarded as a filtering process because the observation data includes the influence of noise and interference in the system. This paper presents an improved adaptive fuzzy Kalman filter. The algorithm establishes a new nonlinear membership function according to the changing characteristics of fuzzy inference input. Aiming at the minimum variance control problem of the system with unknown parameters and random changes, a minimum variance control strategy based on fuzzy theory is proposed This scheme can suppress the divergence of the filter and improve the accuracy of the navigation system when it is used in the process of ship navigation calculation. Simulation results show that the algorithm compensates the influence of incomplete information in data fusion, and has higher accuracy than conventional Kalman filtering.

At present, scholars use multi-sensor fusion technology to "fuse" multiple types of information according to some optimal fusion criteria, which has led to a variety of integrated navigation schemes in the navigation field, such as fiber optic gyroscope strapdown inertial navigation system, low-cost mems/moems gyroscope strapdown inertial navigation system and GPS, glonss, "Beidou" navigation system, and so on. Therefore, the focus of future research is on Kalman filter and the various filters extended from it, which are valued by researchers and widely used in integrated navigation systems, as well as in the case of unknown or time-varying noise of the system. In addition, how to improve the filtering algorithm of integrated navigation system to improve the navigation accuracy of nonlinear system is also the focus of future research.

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