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Research on adaptive information fusion algorithm and its application

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Abstract: The integrated navigation system was taken as research background and an information fusion algorithm based on adaptive federal Kalman filter (AFKF) was studied. ARMA model and self-adapting information sharing factor were applied to federal filter so as to accomplish information fusion. The semi-physical simulation of GPS/INS system is carried out, and the results illustrate that this method can inhibit divergence of filter and improve the accuracy and convergence speed of the whole system.

Key words: information fusion; ARMA model; information sharing; integrated navigation

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自适应信息融合算法研究与应用

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摘要: 以组合导航系统为应用背景,对基于自适应联合卡尔曼滤波的信息融合算法进行了研究,将ARMA模型和自适应调节的信息分配因子应用于联合滤波中,完成信息融合,并以GPS/INS系统为例,进行了半实物仿真,结果表明,该方法可有效抑制滤波发散,并提高整个系统的精度和收敛速度.

关键词: 信息融合; ARMA模型; 信息分配; 组合导航

1 Introduction

With the development of the automation and artificial intelligence, more and more sensors are used in the field of industry, military affairs and scientific research. Each sensor has its own special characteristic and usually describes only a certain aspect of the measured objects. In most cases, the information provided by each sensor might be incomplete, inconsistent, imprecise and even disagree, in some extent, with the information offered by other sensors. So none of them can provide overall and accurate information at any time. To overcome this problem, the multi-sensor combination is proposed and the redundant and complementary information used to improve the accuracy and reliability of the whole system[1~3]. Given the development and application of the information fusion theory at present, the most important thing in this domain is to investigate an algorithm with ability of availability, stability and fault-tolerance.

This paper focuses on a new information fusion algorithm based on AFKF which firstly transform Kalman filter (KF) into autoregressive moving average (ARMA) model, estimate filter gain $K(k)$ directly, instead of $Q(k)$ and $R(k)$, then applies it to the local filters of federal Kalman filter (FKF) to complete information fusion. At last, in order to acquire the best performance of FKF, an adaptive information-sharing criterion is given in response to the error variance of each local filter.

2 Information fusion algorithm based on AFKF

2.1 Optimal estimation based on ARMA

Consider the linear discrete-time system represented by

$$x(k+1) = \Phi x(k) + \Gamma w(k), \tag{1}$$

$$z(k) = Hx(k) + v(k), \tag{2}$$

where $x(k) \in \mathbb{R}^n$ is state vector at time k; $\Phi \in \mathbb{R}^{n\times n}$ is state transition matrix, Γ and H are coefficient matrices,

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$w(k)$ and $v(k)$ are process noise and measurement noise respectively, they are independent, zero-mean, white Gaussian sequences with

$$\begin{cases} \mathrm{E}\,[w(k)] = 0, \\ \mathrm{cov}\,[w(k), w(j)] = \\ \mathrm{E}\,[w(k)w^{\mathrm{T}}(j)] = Q\delta(k,j), \end{cases} \tag{3}$$

$$\begin{cases} \mathrm{E}\,[v(k)] = 0, \\ \mathrm{cov}\,[v(k), v(j)] = \\ \mathrm{E}\,[v(k)v^{\mathrm{T}}(j)] = R\delta(k,j). \end{cases} \tag{4}$$

When Q and R are unknown or incertitude, in order to prevent filter divergence, adaptive technique must be taken to estimate and modify them during the filtering. However, the influence of Q and R can be reflected by the gain matrix K_f, so we can estimate K_f directly instead of Q and R.

The Kalman filter formula of the system described by Eqs.(1)and(2)is

$$\hat{x}(k) = \hat{x}(k/k-1) + K_f\tilde{z}(k), \tag{5}$$

$$\tilde{z}(k) = z(k) - H\hat{x}(k/k-1). \tag{6}$$

K_f is an $n \times m$ filter gain matrix. $\tilde{z}(k)$ is zero-mean, white noise with variance matrix of $Q_{\tilde{z}}$.

The corresponding optimum forecast estimation is

$$\begin{aligned} &\hat{x}(k/k-1) = \Phi\hat{x}(k-1) = \\ &\Phi[\hat{x}(k-1/k-2) + K_f\tilde{z}(k-1)] = \\ &\Phi\hat{x}(k-1/k-2) + K_p\tilde{z}(k-1) = \\ &(I_n - q^{-1}\Phi)^{-1}K_p\tilde{z}(k-1). \end{aligned} \tag{7}$$

q^{-1} is unit backward operator, K_p is the forecast gain matrix:

$$K_p = \Phi K_f \tag{8}$$

according to the Fadeeva[4]

$$(I_n - q^{-1}\Phi)^{-1} = \frac{F(q^{-1})}{a(q^{-1})}, \tag{9}$$

where

$$a(q^{-1}) = \det\,(I_n - q^{-1}\Phi) = a_0 + a_1q^{-1} + \cdots + a_nq^{-n}, \tag{10}$$

$$F(q^{-1}) = \mathrm{adj}\,(I_n - q^{-1}\Phi) = F_0 + F_1q^{-1} + \cdots + F_{n-1}q^{-(n-1)}, \tag{11}$$

$$a_0 = 1,\ a_i = -\frac{1}{i}\mathrm{tr}\,(\Phi F_{i-1}),\ i = 1,2,\cdots,n, \tag{12}$$

$$F_0 = I_n,\ F_i = \Phi F_{i-1} + a_iI_n,\ i = 1,\cdots,n-1. \tag{13}$$

Substituting Eq.(9)into Eq.(7):

$$a(q^{-1})\hat{x}(k/k-1) = F(q^{-1})K_p\tilde{z}(k-1). \tag{14}$$

Left multiplication H at both sides simultaneously,

$$a(q^{-1})H\hat{x}(k/k-1) = HF(q^{-1})K_p\tilde{z}(k-1). \tag{15}$$

At last, ARMA model can be established according to the Eq.(6)and Eq.(15)

$$\begin{aligned} &a(q^{-1})z(k) = \\ &HF(q^{-1})K_p\tilde{z}(k-1) + a(q^{-1})\tilde{z}(k) = \\ &[HF(q^{-1})K_pq^{-1} + a(q^{-1})I_m]\tilde{z}(k) = D(q^{-1})\tilde{z}(k), \end{aligned} \tag{16}$$

where

$$\begin{aligned} &D(q^{-1}) = \\ &HF(q^{-1})K_pq^{-1} + a(q^{-1})I_m = I_m + D_1q^{-1} + \cdots + D_nq^{-n}, \end{aligned} \tag{17}$$

$$D_i = HF_{i-1}K_p + a_iI_m \text{ and supposed that } D_i = 0,\ i > n \tag{18}$$

under the conditions given in (3)and (4), and random assumption of initial value $\hat{x}(1/0)$, the forecast gain matrix is

$$K_p = \begin{bmatrix} HF_0 \\ HF_1 \\ \vdots \\ HF_{n-1} \end{bmatrix}^{\#} \begin{bmatrix} D_1 - a_1I_m \\ D_2 - a_2I_m \\ \vdots \\ D_n - a_nI_m \end{bmatrix}. \tag{19}$$

The pseudo-inverse matrix $M^{\#} = (M^{\mathrm{T}}M)^{-1}M^{\mathrm{T}}$.

In Eq.(19), a_i, F_i are solved in advance according to (12) and (13), D_i also can be calculated using Gevers-Wouters algorithm[4]:

So filter gain matrix and optimal state estimation are acquired at last according to (8)and (5):

$$K_f = \Phi^{-1}K_p, \tag{20}$$

$$\hat{x}(k) = \hat{x}(k/k-1) + \hat{K}_f[z(k) - H\hat{x}(k/k-1)]. \tag{21}$$

The filter error variance matrix P can be calculated according to the white noise error variance matrix, from (2)we get

$$x(k) = H^{\#}[z(k) - v(k)], \tag{22}$$

so the non-recursive optimal filter is deduced from (22)

$$\hat{x}(k/k) = H^{\#}[z(k) - \hat{v}(k/k)], \tag{23}$$

and then

$$P = \mathrm{E}\,[(x(k) - \hat{x}(k/k))(x(k) - \hat{x}(k/k))^{\mathrm{T}}] = H^{\#}\mathrm{E}\,[(\hat{v}(k/k)-v(k))(\hat{v}(k/k)-v(k))^{\mathrm{T}}]H^{\#\mathrm{T}} = H^{\#}P_V H^{\#\mathrm{T}}. \tag{24}$$

P_V is error variance matrix of $\hat{v}(k/k)$.

2.2 Adaptive information sharing criterion

Denote the state estimation and covariance matrix of local filter j as $\hat{x}_j$ and $P_j(j=1,\cdots,N)$ respectively. P_j represents the quality evaluation to the accuracy of filter j, the larger it is, the worse the estimation accuracy of $\hat{x}_j$ is. Based on this consideration, variance matrix P_j could be used as weighted constraint, that is, sharing factor $\beta_j(0 \leqslant \beta_j \leqslant 1)$ can be adaptively adjusted according to the P_j to assure the more precise local optimal estimation play the larger role in the whole system. Define $EDOP_i = \sqrt{\mathrm{tr}\ (P_iP_i^{\mathrm{T}})}$ as precision factor of subsystem j, then

$$\beta_j = \frac{1}{N-1}\cdot\frac{\sum\limits_{k=1,k\neq j}^{N} EDOP_k}{\sum\limits_{k=1}^{N} EDOP_k}. \tag{25}$$

2.3 AFKF algorithm

Apply ARMA model and adaptive information sharing criterion described by (1) ~ (25) into federal Kalman filter which introduced by Carlson[5,6], an information fusion algorithm based on AFKF can be constructed. Firstly $\hat{x}_j$ and P_j are computed in local filter j. Then calculate β_j and complete information fusion according to the minimum mean-square error criterion and information conservation axiom ($\Sigma\beta_j = 1$). At last the final output can be acquired.

3 Simulation study

In order to test the effectiveness and practicality of the method discussed above, the semi-physical simulation of a GPS/INS integrated navigation system has been carried out in this section.

The integrated navigation system includes GPS receiver and inertial measure units, which are made up of gyroscopes, accelerometer, digital force feedback balance loop, navigation computer and input-output interface etc. It can provide normal precision velocity and position information. GPS receiver can output information of velocity, position, pseudorange and carrier phase, etc. according to the algorithm given in Section 2. The simulation conditions and results are given follow:

3.1 Dynamics model

Supposed there are two sensors in the federal Kalman filter, one of which is GPS receiver and the other is INS. Take the geographic coordinate system(east-north-up) as the navigation coordinate system and $X = [x_e, v_e, a_e, x_n, v_n, a_n, x_u, v_u, a_u]^{\mathrm{T}}$ as state variables, in which $x_e, v_e, a_e, x_n, v_n, a_n, x_u, v_u, a_u$ are position, velocity and acceleration in three directions respectively. The GPS/INS integrated navigation system could be described by first-order matrix differential equation, as follows:

$$\dot{x}(t) = A(t)x(t) + G(t)w(k). \tag{26}$$

For the GPS (subsystem 1), state variable x_1 is the same to the whole system, that is $x_1 = x$, the measurement model of GPS is

$$z_1 = H_1x_1 + v_1, \tag{27}$$

where $z_1 = [x_e, v_e, x_n, v_n, x_u, v_u]$ is observation vector and H_1 and v_1 are the observation matrix and noise respectively.

In the same manner, for the INS(subsystem 2), we have $x_2 = x$, and $z_2 = H_2x_2 + v_2$. z_2, H_2, v_2 have the same meaning of z_1, H_1, v_1.

3.2 Simulation result

It is assumed that initial position is (45.74°, 126.62°), initial position error is 20 m, velocity error is 1.0 m/s, acceleration error is 0.5 m/s^2. The total simulation time is 1500 s.

The position error and velocity error of GPS/INS integrated navigation system which uses AFKF and general Klaman Filter shown in Figs.1,2 respectively. The dash denotes the result of the general KF and solid line denotes the result of the AFKF. Plots shown in Fig.1 illustrate the convergence for the errors in position. The position error converges to less than 5 m in 150 s, near to 1500 s, and the position errors less than 2 m in magnitude. From these results, it can be seen that the AFKF is effective because of the reduction of the convergent time and improvement of accuracy under the same condition.

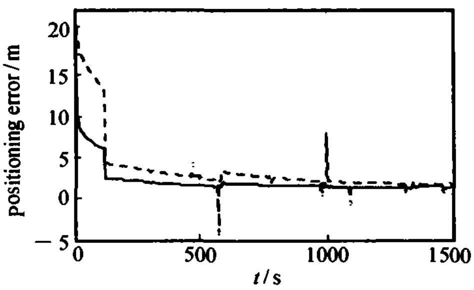

Fig. 1 Positioning error comparison

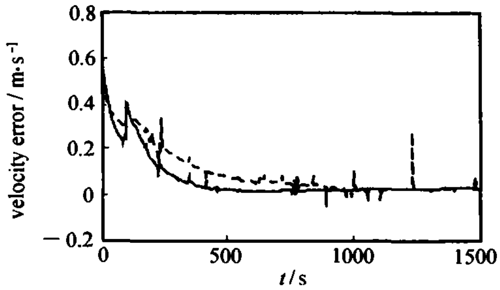

Fig. 2 Velocity error comparison

4 Conclusion

The application of multi-sensor information fusion become more and more widespread in the military and industry nowadays and reveal its superiority and significance. To excogitate and research an effective algorithm is a key problem in the information fusion system. This paper describes an adaptive federal Kalman filter algorithm aiming at integrated navigation system with uncertain parameters. In this research, the system ARMA model is described and adaptive information sharing criterion of federal filter is introduced. This method preserves both the statistical optimality and the recursive computational scheme of the KF and has good potential in other real-time application and fault-tolerance. The simulation results of GPS/INS indicate that this method can restrain filter divergence effectively, and at the same time improve the convergence and calculation speed of the whole system.

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