Multisensor Distributed Track Fusion Algorithm Based on Strong Tracking Filter and Feedback Integration[1)]

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Abstract A new multisensor distributed track fusion algorithm is put forward based on combining the feedback integration with the strong tracking Kalman filter. Firstly, an effective tracking gate is constructed by taking the intersection of the tracking gates formed before and after feedback. Secondly, on the basis of the constructed effective tracking gate, probabilistic data association and strong tracking Kalman filter are combined to form the new multisensor distributed track fusion algorithm. At last, simulation is performed on the original algorithm and the algorithm presented.

Key words Strong tracking filtering, track association, feedback integration, tracking gate, state estimation

1 Introduction

Multisensor track fusion based on feedback is one of the key methods for distributed data fusion. The main ideas can be illustrated as follows [1]. Firstly, each sensor uses one-step state prediction and covariance matrix from a fusion center to create tracking gate, and constructs its local target track based on the tracking gate and Kalman filter, which is then sent to the fusion center. Secondly, the local target tracks from different sensors are associated and fused in the center to form for every target the final target track in the sense of over-all minimum mean square, one-step state prediction and covariance matrix which are fed back to every sensor for next estimation. The research has achieved a lot of breakthroughs in fusion tracking theory and its application[1~4].

Kalman filter or EKF (extended Kalman filter) is the basic characteristic for the fusion algorithm mentioned above. The standard Kalman filter requires that the equations of the system state and the measurement be linear, and that the noises of the system and the measurement be uncorrelated white noise sequences with zero means. But the system model is usually nonlinear due to the complexity of the problem appearing in the real application. Although EKF is one of the effective methods in dealing with the nonlinear filtering, its robust is not good for model uncertainty, which will result in inaccurate system state estimation, even state estimation divergence[5]. In order to overcome the above EKF′s drawbacks, [6~9] present a STF (strong tracking filter) method that can effectively solve the problem of the state inaccurate estimation resulted from the system model uncertainty.

Kalman filter has a strong influence on the multisensor track fusion algorithm based on feedback. In addition, each sensor only makes use of one-step state prediction and covariance matrix to create new tracking gate, without considering the influence of the tracking gates formed before the feedback. In order to solve the problem, an effective tracking gate is constructed by taking the intersection of the tracking gates formed before and after

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feedback. And then the probabilistic data association (PDA) is combined with STF to form the new multi-sensor distributed track fusion algorithm based on the constructed effective tracking gate.

2 System description

The dynamic state model of an object is described as the following[9]

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

where $k \geqslant 0$ is the discrete time variable, $x \in R^{n \times 1}$ is the state variable of interest, $\Gamma(k) \in R^{n \times q}$ is the known matrix, the system noise $w(k) \in R^{q \times 1}$ is a stochastic process, and the nonlinear function $f: R^n \rightarrow R^n$ has first-order continuous partial differential coefficients over the states.

With the following measurement equation, the state variables of the same object are observed by N different sensors respectively.

$$z_i(k) = h_i(k, x(k)) + v_i(k), \quad i = 1, 2, \cdots, N \tag{2}$$

where $z_i(k) \in R^{d_i \times 1} (d_i \leqslant n)$ is the measurement variable, the measurement noise $v_i(k) \in R^{d_i \times 1}$ is a stochastic process, and the nonlinear function $h_i: R^{d_i} \rightarrow R^{d_i}$ has first-order continuous partial differential coefficients over the states.

The noises of the system and the measurement are the uncorrelated stochastic white noise sequence with

$$E\{w(k)\} = \mathbf{0} \tag{3}$$

$$E\{w(k) w^{\mathrm{T}}(l)\} = Q(k) \delta_{kl}, \quad k, l > 0 \tag{4}$$

$$E\{v_i(k)\} = \mathbf{0} \tag{5}$$

$$E\{v_i(k) v_j^{\mathrm{T}}(l)\} = R_i(k) \delta_{ij} \delta_{kl}, \quad i, j = 1, 2, \cdots, N, \ k, l > 0 \tag{6}$$

$$E\{v_i(k) w^{\mathrm{T}}(l)\} = 0, \quad i = 1, 2, \cdots, N, \ k, l \geqslant 0 \tag{7}$$

where $Q(k)$ is a symmetrical nonnegative matrix, and $R_i(k)$ is a symmetric positive matrix.

It is assumed that the initial value $x(0)$ of the state vectors $x(k)$, $w(k)$, $v_i(k)$ are independent of each other, and $x(0)$ is a Gaussian random vector with statistics

$$E\{x(0)\} = x_0 \tag{8}$$

$$E\{[x(0) - x_0][x(0) - x_0]^{\mathrm{T}}\} = P_0 \tag{9}$$

3 Track fusion algorithm based on the feedback integration and STF

3.1 Fusion algorithm

The time-variant fading factor[8] introduced in EKF adjusts the covariance matrix of the state prediction errors and the corresponding gain matrix in-line to make the residual error sequence keep orthogonality when the variance of the state estimation errors reaches the minimum. This is the basic idea of STF that can ensure the robusticity of the filter for the system model uncertainty and the strong tracking ability all the time for the slowly changing and abruptly changing states.

As for the system described in (1) and (2), assume that we have obtained the estimate $\hat{x}(k|k)$ for state $x(k)$ based on global information and the corresponding estimation error covariance matrix $P(k|k)$ at time k. When we get the actual measurements for $x(k+1)$ from every sensor, we can obtain the fusion estimate at time $k+1$ based on global information

$$\hat{x}(k+1 \mid k+1) = \hat{x}(k+1 \mid k) +$$

$$P(k+1 \mid k+1) \Big\{ \sum_{i=1}^{N} P_i^{-1}(k+1 \mid k+1)[\hat{x}_i(k+1 \mid k+1) - \hat{x}_i(k+1 \mid k)] -$$

$$\sum_{i=1}^{N} P_i^{-1}(k+1 \mid k)[\hat{\boldsymbol{x}}_i(k+1 \mid k) - \hat{\boldsymbol{x}}(k+1 \mid k)]\Big\} \tag{10}$$

and its fusion estimation error covariance is

$$P^{-1}(k+1 \mid k+1) = P^{-1}(k+1 \mid k) + \sum_{i=1}^{N}[P_i^{-1}(k+1 \mid k+1) - P_i^{-1}(k+1 \mid k)] \tag{11}$$

In (10) $\hat{\boldsymbol{x}}(k+1|k)$is one-step prediction estimation based on global information

$$\hat{\boldsymbol{x}}(k+1 \mid k) = \boldsymbol{f}(k, \hat{\boldsymbol{x}}(k \mid k)) \tag{12}$$

$\hat{\boldsymbol{x}}_i(k+1|k)$is one-step prediction estimation based on ith sensor

$$\hat{\boldsymbol{x}}_i(k+1 \mid k) = \boldsymbol{f}(k, \hat{\boldsymbol{x}}_i(k \mid k)) \tag{13}$$

$P_i(k+1|k)$ is one-step prediction error covariance for the ith sensor on the basis of STF ($\lambda_i(k)$ is a suboptimal fading factor whose setting method will be discussed in the following section)

$$P_i(k+1 \mid k) = \lambda_i(k)F_i(k)P_i(k \mid k)F_i^{\mathrm{T}}(k) + \Gamma(k)Q(k)\Gamma(k) \tag{14}$$

In (11), $P(k+1|k)$ is one-step prediction error covariance on the basis of global information

$$P(k+1 \mid k) = F(k)P(k \mid k)F^{\mathrm{T}}(k) + \Gamma(k)Q(k)\Gamma(k) \tag{15}$$

Let $\hat{\boldsymbol{x}}_i(k+1|k+1)$ and $P_i(k+1|k+1)$ be the local state estimation and error covariance based on ith sensor respectively. According to [10~12], the target state estimation for ith sensor can be obtained by means of PDAalgorithm[1]

$$\hat{\boldsymbol{x}}_i(k+1 \mid k+1) = \sum_{j=0}^{m_i(k+1)} \beta_i^j \hat{\boldsymbol{x}}_i^j(k+1 \mid k+1) = \hat{\boldsymbol{x}}_i(k+1 \mid k) + K_i(k+1)\boldsymbol{y}_i(k+1 \mid k) \tag{16}$$

$$P_i(k+1|k+1) = \beta_i^0(k+1)P_i(k+1|k)[1-\beta_i^0(k+1)][I-K_i(k+1)H_i(k+1)]P_i(k+1|k) + K_i(k+1)\{\sum_{j=1}^{m_i(k+1)} \beta_i^j(k)\boldsymbol{y}_i^j(k+1)(\boldsymbol{y}_i^j)^{\mathrm{T}} - \boldsymbol{y}_i(k+1)(\boldsymbol{y}_i(k+1))^{\mathrm{T}}\}(K_i(k+1))^{\mathrm{T}} \tag{17}$$

In (16) and (17) $K_i(k+1)$ is the gain matrix, $\boldsymbol{y}_i(k+1|k)$ is the probabilistic sum of one-step measurement prediction errors for the ith sensor

$$K_i(k+1) = P_i(k+1 \mid k)(H_i(k+1))^{\mathrm{T}}[H_i(k+1)P_i(k+1)(H_i(k+1))^{\mathrm{T}} + R_i(k+1)]^{-1} \tag{18}$$

$$\boldsymbol{y}_i(k+1) = \sum_{j=0}^{m_i(k+1)} \beta_i^j \boldsymbol{y}_i^j(k+1) \tag{19}$$

$$\boldsymbol{y}_i^j(k+1) = \boldsymbol{z}_i^j(k+1) - \hat{\boldsymbol{z}}_i(k+1 \mid k) \tag{20}$$

$$\hat{\boldsymbol{z}}_i(k+1 \mid k) = \boldsymbol{h}_i(k+1, \hat{\boldsymbol{x}}_i(k+1 \mid k)) \tag{21}$$

From (16) to (21), $m_i(k+1)$ is the number of returns at time $k+1$ in the ith tracking gate, $\boldsymbol{z}_i^j(k+1)$ is the jth return fallen into the ith tracking gate at time $k+1$, $\hat{\boldsymbol{z}}_i(k+1|k)$ is the one-step prediction measurement estimation based on the ith sensor, $\beta_i^j(k+1)$ denotes the probability of the $\boldsymbol{z}_i^j(k+1)$ from the target, and $\beta_i^0(k+1)$ denotes the probability of the event that there is no measurement coming from the target in the ith tracking gate.

One-step measurement prediction error covariance based on ith sensor is

$$S_i(k+1) = H_i(k+1)P_i(k+1|k)(H_i(k+1))^{\mathrm{T}} + R_i(k+1) \tag{22}$$

and one-step measurement prediction error covariance on the basis of global information is

$$S_i^0(k+1) = H_i^0(k+1)P(k+1|k)(H_i^0)^{\mathrm{T}}(k+1) + R_i(k+1) \tag{23}$$

where in (17)~(27)

$$H_i(k+1) = \frac{\partial \boldsymbol{h}_i(k+1, \boldsymbol{x}(k+1))}{\partial \boldsymbol{x}}\bigg|_{\boldsymbol{x}(k+1)=\hat{\boldsymbol{x}}_i(k+1|k)} \tag{24}$$

$$H_i^0(k+1) = \left.\frac{\partial \boldsymbol{h}_i(k+1,\boldsymbol{x}(k+1))}{\partial \boldsymbol{x}}\right|_{x(k+1)=\hat{x}(k+1|k)} \tag{25}$$

$$F_i(k) = \left.\frac{\partial f(k,\boldsymbol{x}(k))}{\partial \boldsymbol{x}}\right|_{x(k)=x_i(k|k)} \tag{26}$$

$$F(k) = \left.\frac{\partial f(k,\boldsymbol{x}(k))}{\partial \boldsymbol{x}}\right|_{x(k)=x(k|k)} \tag{27}$$

3.2 Setting the fading factor

In order to decrease the computational load and ensure the on-line performance of the algorithm, the approximation method presented in [7] is adopted to set the suboptimal fading factor $\lambda_i(k)$, shown as the following.

$$\lambda_i(k+1) = \begin{cases}\lambda_i, & \lambda_i \geqslant 1, \\ 1, & \lambda_i < 1\end{cases} \quad i = 1,2,3\cdots N \tag{28}$$

$$\lambda_i = \frac{tr[N_i(k+1)]}{tr[M_i(k+1)]} \tag{29}$$

$$\begin{aligned} N_i(k+1) = & V_i(k+1) - H_i(k+1,\hat{\boldsymbol{x}}_i(k+1 \mid k))\Gamma(k)Q(k+1)\Gamma^{\mathrm{T}}(k) \cdot \\ & H_i^{\mathrm{T}}(k+1,\hat{\boldsymbol{x}}_i(k+1 \mid k)) - \alpha R_i(k+1) \end{aligned} \tag{30}$$

$$\begin{aligned} M_i(k+1) = & H_i(k+1,\hat{\boldsymbol{x}}_i(k+1 \mid k))F_i(k,\hat{\boldsymbol{x}}_i(k \mid k))P(k|k) \cdot \\ & F_i^{\mathrm{T}}(k,\hat{\boldsymbol{x}}_i(k \mid k))H_i^{\mathrm{T}}(k+1,\hat{\boldsymbol{x}}_i(k+1 \mid k)) \end{aligned} \tag{31}$$

$$V_i(k+1) = \begin{cases} \boldsymbol{y}_i(1)\boldsymbol{y}_i^{\mathrm{T}}(1), & k = 0 \\ \dfrac{\rho V_i(k) + \boldsymbol{y}_i(k+1)\boldsymbol{y}_i^{\mathrm{T}}(k+1)}{1+\rho}, & k \geqslant 1 \end{cases} \tag{32}$$

where $0 \leqslant \rho \leqslant 1$ is a forgetting factor chosen to be $\rho = 0.95$ in common use, $\alpha \geqslant 1$ is a given weakened factor.

3.3 Setting the effective tracking gate

Target tracks formed at time k in local are sent to the fusion center where these tracks are fused to form the fused track of the target, the target state prediction $\hat{\boldsymbol{x}}(k+1|k)$ and the covariance matrix $P(k+1|k)$ which are fed back to every local sensor $i(i=1,2,\cdots,N)$.

Let $Y_i^a(k+1)$ denote the effective return set of the ith sensor at time $k+1$ before feedback. $Y_i^a(k+1)$ satisfies[6,13]

$$\begin{aligned} Y_i^a(k+1) = \{ & \boldsymbol{z}_i^j(k+1) \mid [\boldsymbol{z}_i^j(k+1) - \hat{\boldsymbol{z}}_i(k+1|k)]^{\mathrm{T}}[S_i(k+1)]^{-1} \\ & [\boldsymbol{z}_i^j(k+1) - \hat{\boldsymbol{z}}_i(k+1|k)] < \gamma^2 \} \end{aligned} \tag{33}$$

where γ is the threshold of the tracking gate.

Let $Y_i^b(k+1)$ denote the effective return set of the ith sensor at time $k+1$ after feedback. $Y_i^b(k+1)$ satisfies

$$\begin{aligned} Y_i^b(k+1) = \{ & \boldsymbol{z}_i^j(k+1) \mid [\boldsymbol{z}_i^j(k+1) - \hat{\boldsymbol{z}}_i^0(k+1|k)]^{\mathrm{T}}[S_i^0(k+1)]^{-1} \\ & [\boldsymbol{z}_i^j(k+1) - \hat{\boldsymbol{z}}_i^0(k+1|k)] < \gamma^2 \} \end{aligned} \tag{34}$$

where $\hat{\boldsymbol{z}}_i^0(k+1|k) = \boldsymbol{h}_i(k+1,\hat{\boldsymbol{x}}(k+1|k))$ is the one-step measurement prediction for the ith sensor based on the global information. Thus, the final effective return set symbolized as $\tilde{Y}_i(k+1)$ for the ith sensor at time $k+1$ is

$$\tilde{Y}_i(k+1) = Y_i^a(k+1) \cap Y_i^b(k+1) \tag{35}$$

According to the fusion algorithm presented in Section 3.1, the next local and global state estimations are repeated by taking $\tilde{Y}_i(k+1)$ as the final effective return set, $P_i(k+1|k) = P(k+1|k)$, and $\boldsymbol{x}_i(k+1|k) = \hat{\boldsymbol{x}}(k+1|k)$.

4 Simulation research

Given that 2 radars located on the same motion platform synchronously observe a certain region of 65km×80km×70km with a 0.5 seconds sampling period. Radar1 observations satisfy a Gaussian distribution with null average and 6 mrd standard deviation both for azimuth and elevation and 90m standard deviation for range, while Radar2 observations satisfy a Gaussian distribution with null average and 5 mrd standard deviation both for azimuth and elevation and 80m standard deviation for range. Their measurement equations are

$$z_i(k) = \begin{bmatrix} \mathrm{tg}^{-1}(x_2(k)/x_1(k)) \\ \mathrm{tg}^{-1}(x_3(k)/\sqrt{x_1^2(k)+x_2^2(k)}) \\ \sqrt{x_1^2(k)+x_2^2(k)+x_3^2(k)} \end{bmatrix} + v_i(k), \quad i = 1,2 \tag{36}$$

The threshold of the tracking gate is $\gamma = \sqrt{9.2}$, and the uniform clutter density is chosen as $0.2/\mathrm{Km}^2$. In the observation region, there is an aggressive target with the initial position $x(0) = [x_1(0), x_2(0), x_3(0)]^T = [15\mathrm{km}, 15\mathrm{km}, 15\mathrm{km}]^T$ moving in the 3-D area with the same fixed altitude $x_3(k) = 15\mathrm{km}$, and lasting for 100 seconds. Its state equations are

$$\begin{aligned} x_1(k+1) &= x_1(k) - 0.01 \times a \times x_1^2(k) + w_1(k) \\ x_2(k+1) &= b \times x_2(k) + w_2(k) \\ x_3(k+1) &= x_3(k) + w_3(k) \end{aligned} \tag{37}$$

where $a = 0.35$, $b = 0.98$; $w_1(k)$, $w_2(k)$ and $w_3(k)$ are Gaussian distributions with null average and 40m standard deviation.

Select $\alpha = 1.1$, and denote $G(t)$ as the real trajectory of the target, $G_1(t)$ and $G_2(t)$ as the multisensor distributed fused trajectories of the target based on the EKF and feedback, as well as based on STF and feedback integration respectively. The simulation results are shown in Fig. 1, Fig. 2, and Table 1.

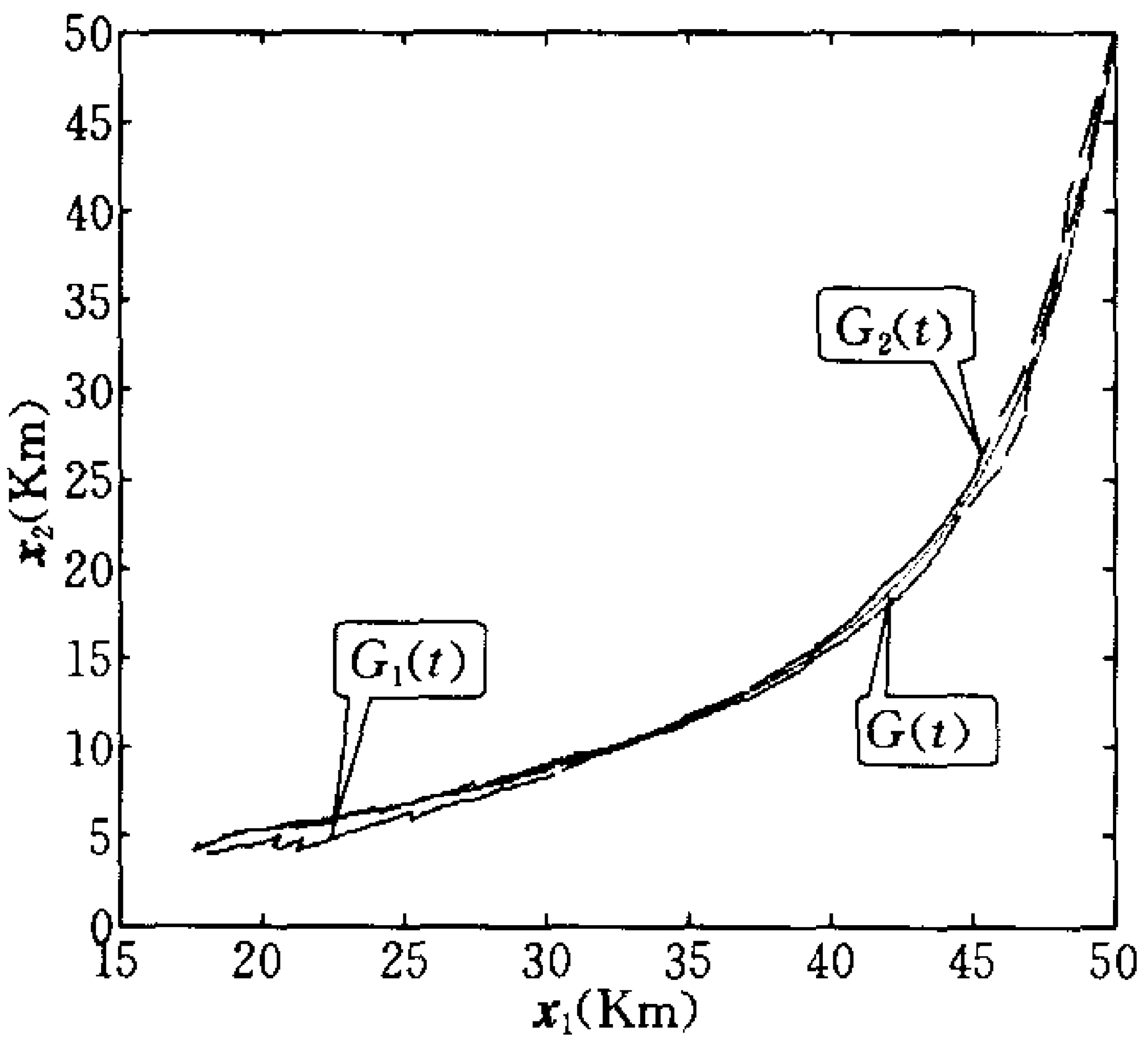

Fig. 1 Simulation result when the model parameters are matched with the system parameters

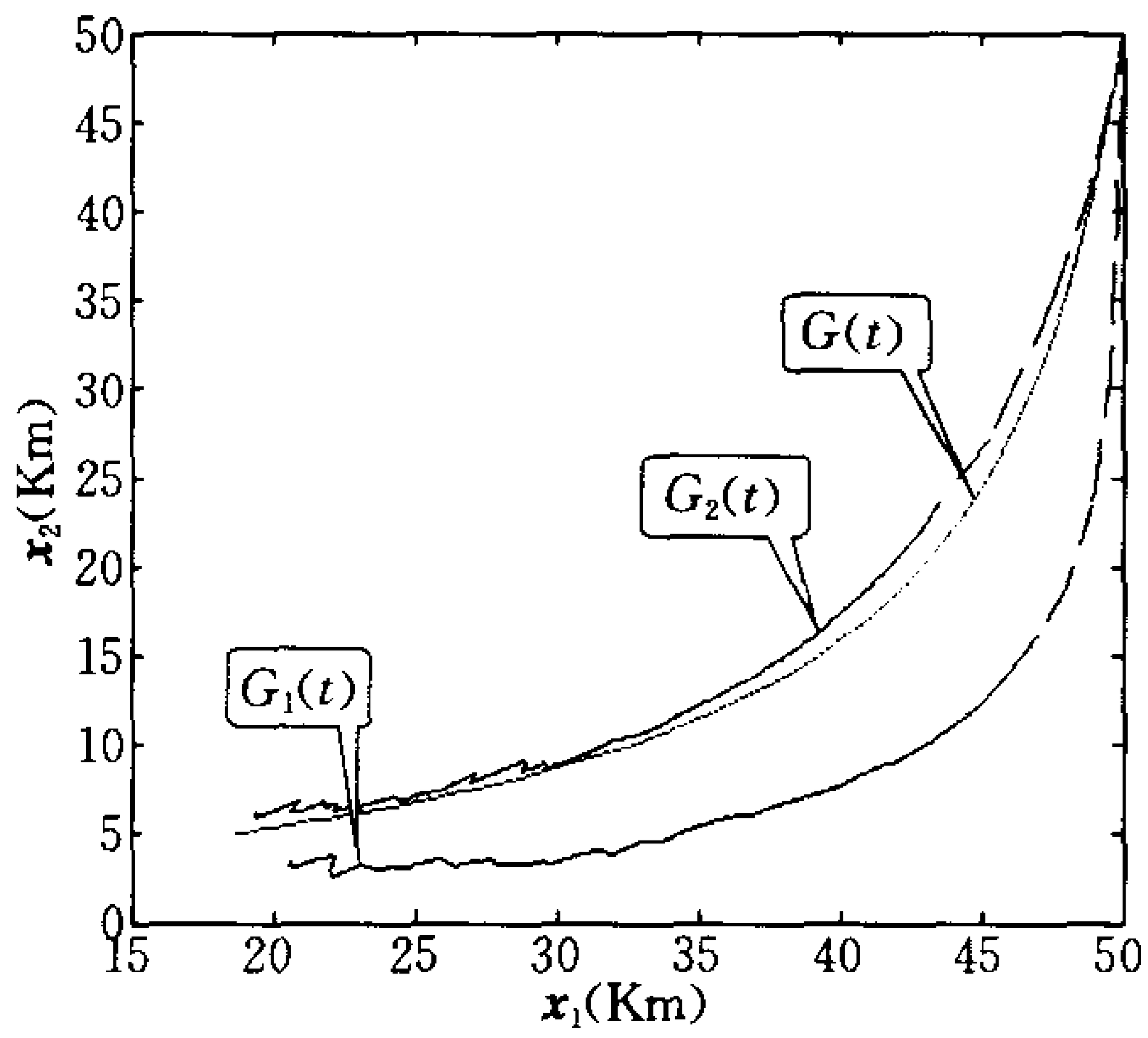

Fig. 2 Simulation result when the model parameters are not matched with the system parameters

Table 1 Prediction positions and returns fallen into different tracking gates

		Radar1	Radar2
feedback Before	Position prediction based on local	(8. 9036,29. 4769,49. 5124)	
	Returns fallen into the tracking gate	(8. 012,31. 3302,49. 3124) (9. 0739,29. 6091,49. 7416) (10. 1713,28. 4281,50. 5124)	(8. 1045,30. 6702,49. 4519) (9. 1031,29. 9103,49. 8977) (10. 0965,28. 98123,50. 0152)
feedback After	Position prediction based on global	(9. 1534,30. 2734,50. 4512)	
	Returns fallen into the tracking gate	(8. 2763,28. 0100,50. 0124) (9. 0739,29. 6091,49. 7416) (11. 1135,31. 2468,52. 1134)	(8. 6724,28. 7810,50. 4812) (9. 1031,29. 9103,49. 8977) (11. 1135,31. 2468,52. 1134)
Feedback integration	Returns fallen into the tracking gate	(9. 0739,29. 6091,49. 7416) (9. 1031,29. 9103,49. 8977)	(9. 0739,29. 6091,49. 7416) (9. 1031,29. 9103,49. 8977)

When the model parameters are matched with the system parameters, it can be seen from Fig. 1that the multisensor distributed track fusion algorithm based on STF and the feedback integration has very approximately the same tracking effect as the one based on EKF and feedback. In addition, Tab. 1 shows the target returns fallen into different tracking gates at time $k=25$(it is known through simulation that the number of the target returns reaches the maximum at this time). It can be seen from Tab. 1 that the target returns fallen into the tracking gate after feedback integration is obviously decreased. This will reduce the computational load of the local PDA algorithm effectively. As a result, the on-line tracking performance of the whole system has been improved.

Fig. 2 shows the simulation result when the model parameters are not matched with the system parameters. a is increased from 0.35 to 0.68, while b is decreased from 0.98 to 0.88. It can be seen from Fig. 2 that large state estimation errors appear when the multisensor distributed track fusion algorithm based on EKF and feedback is applied. But the multisensor distributed track fusion algorithm based on STF and the feedback integration has the strong state estimation ability. This demonstrates that the fusion algorithm based on STF and the feedback integration has strong robustness for the system model uncertainty.

5 Conclusion

Considering the limitation of Kalman filter in the real application, STF is introduced into the multisensor distributed fusion field on the basis of [8,9]. With the help of the final effective tracking gate constructed by taking the intersection of the tracking gates formed before and after feedback, a new multi-sensor distributed track fusion algorithm combining the feedback integration with the strong tracking Kalman filter is put forward in this paper. Simulations are performed on the fusion algorithm based on EKF and feedback as well as the one based on STF and the feedback integration. The simulation result shows that the fusion algorithm based on STF and the feedback integration: 1) can reduce the computational load of the local PDA algorithm effectively to improve the on-line tracking performance of the whole system; 2) has strong robustness for the system model uncertainty.

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基于强跟踪滤波和反馈综合的多传感器分布式航迹融合

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摘　要　研究基于强跟踪滤波和反馈综合相结合的多传感器分布式航迹融合算法.首先,以反馈前后形成的跟踪门的交集构造有效跟踪门.然后,将强跟踪卡尔曼滤波和概率数据关联算法相结合,利用构造的有效跟踪门,提出了一种新的多传感器分布式航迹融合算法.最后,对原有算法和所提算法进行了仿真研究.

关键词　强跟踪滤波,航迹融合,反馈综合,跟踪门,状态估计

中图分类号　TN941