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Distributed H_∞ fusion filter design for INS/WSN integrated positioning system

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Abstract: In order to keep stable navigation accuracy when the blind node (BN) moves between two adjacent clusters, a distributed fusion method for the integration of the inertial navigation system (INS) and the wireless sensor network (WSN) based on H_∞ filtering is proposed. Since the process and measurement noise in the integration system are bounded and their statistical characteristics are unknown, the H_∞ filter is used to fuse the information measured from local estimators in the proposed method. Meanwhile, the filter can yield the optimal state estimate according to certain information fusion criteria. Simulation results show that compared with the federal Kalman solution, the proposed method can reduce the mean error of position by about 45% and the mean error of velocity by about 85%.

Key words: inertial navigation system; wireless sensor network; H_∞ filter; distributed fusion

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The global positioning system (GPS)/inertial navigation system (INS) integration can provide superior performance in comparison with either a GPS or an INS stand-alone system. However, the performance of the GPS-based integrated systems depends on the accuracy of GPS solution, which may encounter problems in urban and indoor environments[1–2]. Thus, the development of the wireless sensor network (WSN) has greatly encouraged the use of sensors in the GPS-outage area. For instance, in order to achieve continuous position determination, Retscher et al.[3] employed RFID to correct the errors of the INS as the GPS does. Aiming at the poor measurement information observability of traditional loosely positioning methods, Xu et al.[4] proposed a tightly-coupled integrated positioning model of the WSN/INS based on the Kalman filter (KF). However, the traditional KF has difficulty in solving the problems for the integrated positioning system with unknown statistical characteristics of measurement noise such as correlated random noise, bias instability and angle random walk and so on. In order to solve these problems, some researchers attempt to use the H_∞ filtering technique since the exogenous input signal in the H_∞ setting is assumed to be energy bounded rather than Gaussian[5–8]. Meanwhile, the method proposed by Xu et al.[4] is actually centralized fusion, and the data measured by sensors need to be transmitted to a computing center for processing. It is bound to create large network traffic which may increase the risk of network congestion. It can also result in severe computational overhead due to overloading of the filter with more data than that it can handle. Since the H_∞ filter is designed such that the H_∞ norm of the system, which reflects the worst-case "gain" that the filter has, is minimized, it also has been widely used to cope with disturbances of partially unknown statistics but with an upper bound of the signal power[9–12].

In order to keep stable navigation accuracy when the BN moves between two adjacent clusters, a distributed H_∞ fusion method for INS/WSN integrated positioning is proposed. In this method, the H_∞ filter is used to estimate errors of position and velocity for the INS/WSN integrated positioning system while the WSN is designed by distributed clustering network. The filter that fuses the information from local estimators can yield the optimal state estimate according to certain information fusion criteria. A simulation experiment is performed to evaluate the performance of the proposed method, and the results show its effectiveness.

1 Structure of the INS/WSN Integration

The structure of the distributed H_∞ fusion filter for the INS/WSN integration is shown in Fig. 1. In order to reduce the network traffic, the RNs in the WSN are grouped by different clusters, and each cluster has a head node used to communicate with adjoining clusters and the

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fusion center. The velocity and the position of the BN are measured by the INS and the WSN, respectively. Thus, the errors among measurement information are independent and not relevant. The distributed fusion filter accepts the difference values of the velocity and the position measured by the INS and those measured by the WSN as measurement information.

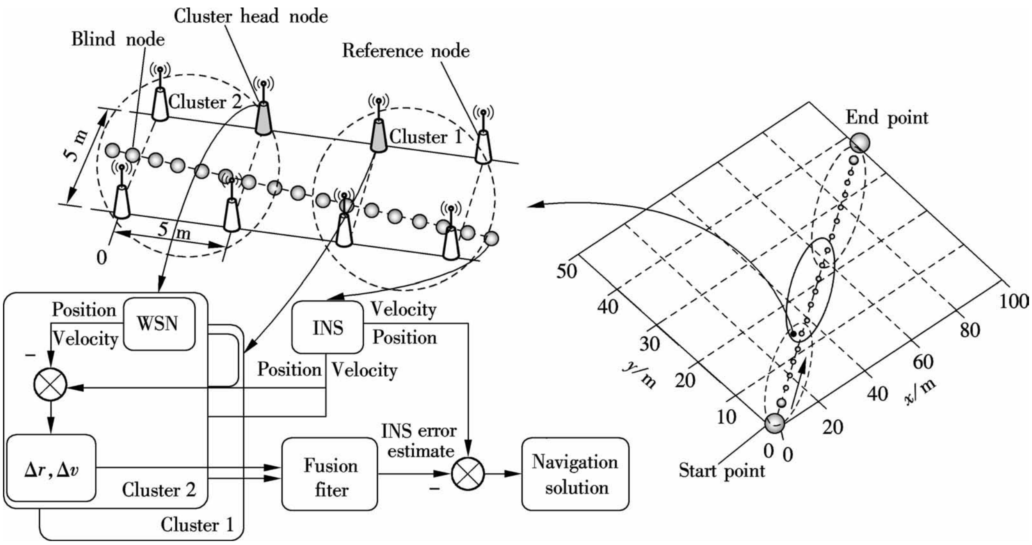

Fig. 1 The structure of INS/WSN integrated positioning

The following stochastic discrete time system model is considered for the whole INS/WSN integrated positioning system in one cluster of the WSN.

$$\left.\begin{aligned} \boldsymbol{x}_{c,k+1} &= \boldsymbol{A}_c \boldsymbol{x}_{c,k} + \boldsymbol{B}_c \boldsymbol{w}_{c,k} \\ \boldsymbol{y}_{c,k} &= \boldsymbol{C}_c \boldsymbol{x}_{c,k} + \boldsymbol{D}_c \boldsymbol{\xi}_{c,k} \\ z_{c,k} &= \boldsymbol{L}_c \boldsymbol{x}_{c,k} \qquad k = 0, 1, 2, \dots \end{aligned}\right\} \tag{1}$$

where $\boldsymbol{x}_{c,k} \in \mathbf{R}^n$ is the c-th cluster system state, $\boldsymbol{x}_{c,k} = [e_{c,x,k} \quad e_{c,y,k} \quad e_{c,vx,k} \quad e_{c,vy,k}]^{\mathrm{T}}$; $(e_{c,x,k}, e_{c,y,k})$ and $(e_{c,vx,k}, e_{c,vy,k})$ are the position and velocity errors of the BN, respectively; $\boldsymbol{y}_{c,k} \in \mathbf{R}^{l_c}$ ($c = 1, 2, \dots, N$) is the c-th measurement output in the c-th cluster, $\boldsymbol{y}_{c,k} = [\Delta r_{c,x,k} \quad \Delta r_{c,y,k} \quad \Delta v_{c,x,k} \quad \Delta r_{c,y,k}]^{\mathrm{T}}$; $(\Delta r_{c,x,k}, \Delta r_{c,y,k})$ and $(\Delta v_{c,x,k}, \Delta v_{c,y,k})$ are differences between the position and velocity errors of the BN measured by INS and those measured by the c-th cluster in WSN; $\boldsymbol{\xi}_{c,k}$ is the measurement noise which belongs to $l_2[0, \infty)$; $\boldsymbol{w}_{c,k} \in \mathbf{R}^m$ is stochastic process noise which also belongs to $l_2[0, \infty)$; $z_{c,k} \in \mathbf{R}^r$ is the state combination to be estimated; $\boldsymbol{B}_{\mathrm{c}}$, $\boldsymbol{C}_{\mathrm{c}}$, $\boldsymbol{D}_{\mathrm{c}}$ and $\boldsymbol{L}_c$ are the constant matrices of the appropriate dimensions. $\boldsymbol{A}_c$ in Eq. (1) can be expressed as

$$\boldsymbol{A}_c = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{2}$$

where T is the sampling time.

For convenience, in order to construct the fusion filter, system (1) can be rewritten as

$$\left.\begin{aligned} \boldsymbol{x}_{c,k+1} &= \boldsymbol{A}_c \boldsymbol{x}_k + \boldsymbol{B}_{c1} \boldsymbol{\zeta}_{c,k} \\ \boldsymbol{y}_{c,k} &= \boldsymbol{C}_c \boldsymbol{x}_k + \boldsymbol{D}_{c1} \boldsymbol{\zeta}_{c,k} \\ z_{c,k} &= \boldsymbol{L}_c \boldsymbol{x}_{c,k} \qquad k = 0, 1, 2, \dots \end{aligned}\right\} \tag{3}$$

where $\boldsymbol{B}_{c1} = [\boldsymbol{B}_c \quad \boldsymbol{0}]$, $\boldsymbol{D}_{c1} = [\boldsymbol{0} \quad \boldsymbol{D}_c]$, and $\boldsymbol{\zeta}_{c,k} = [\boldsymbol{w}_{c,k}^{\mathrm{T}} \quad \boldsymbol{\xi}_{c,k}^{\mathrm{T}}]^{\mathrm{T}}$.

Now, the H_∞ filter for the c-th cluster measurement system is built as

$$\left.\begin{aligned} \hat{\boldsymbol{x}}_{c,k+1} &= \boldsymbol{A} \hat{\boldsymbol{x}}_{c,k} + K_c(\boldsymbol{y}_{c,k} - \boldsymbol{C}_c \hat{\boldsymbol{x}}_{c,k}) \\ \hat{z}_{c,k} &= \boldsymbol{L}_c \hat{\boldsymbol{x}}_{c,k} \end{aligned}\right\} \tag{4}$$

where $\hat{\boldsymbol{x}}_{c,k} \in \mathbf{R}^n$, $\hat{z}_{c,k} \in \mathbf{R}^r$ are the estimations of $\boldsymbol{x}_{c,k}$ and $z_{c,k}$, respectively, and $\boldsymbol{K}_c$ is the Kalman gain. Let $\tilde{\boldsymbol{x}}_{c,k} = \boldsymbol{x}_{c,k} - \hat{\boldsymbol{x}}_{c,k}$, $\tilde{z}_{c,k} = z_{c,k} - \hat{z}_{c,k}$, and we can obtain

$$\left.\begin{aligned} \tilde{\boldsymbol{x}}_{c,k+1} &= \widetilde{\boldsymbol{A}}_c \tilde{\boldsymbol{x}}_{c,k} + \widetilde{\boldsymbol{B}}_c \boldsymbol{\zeta}_{i,k} \\ \tilde{z}_{c,k} &= z_{c,k} - \hat{z}_{c,k} = \boldsymbol{L}_c \tilde{\boldsymbol{x}}_{c,k} \end{aligned}\right\} \tag{5}$$

where $\widetilde{\boldsymbol{A}}_c = \boldsymbol{A}_c - \boldsymbol{K}_c \boldsymbol{C}_c$, $\widetilde{\boldsymbol{B}}_c = \boldsymbol{B}_1 - \boldsymbol{K}_c \boldsymbol{D}_{c1}$. For the whole distributed fusion system, the global system state estimator $\hat{\boldsymbol{x}}_k \in \mathbf{R}^n$ for $\boldsymbol{x}_k$ should satisfy

$$\hat{\boldsymbol{x}}_k = \sum_{c=1}^{N} \boldsymbol{M}_c \hat{\boldsymbol{x}}_{c,k} \tag{6}$$

where $\boldsymbol{M}_c$ ($c = 1, 2, \dots, N$) are the weighted matrices, they should satisfy

$$\sum_{i=1}^{N} \boldsymbol{M}_i = \boldsymbol{I} \tag{7}$$

The performance index for a given scalar $\gamma_c > 0$ for Eq. (5) is defined as

$$J_c = E\sum_{k=0}^{\infty}(\tilde{z}_{c,k}^{\mathrm{T}}\tilde{z}_{c,k} - \gamma^2\zeta_{c,k}^{\mathrm{T}}\zeta_{c,k}) \qquad c = 1,2,\ldots,N \tag{8}$$

For the distributed H_∞ fusion filter, we seek estimators from the system Eq. (4) such that for each nonzero $\zeta_{c,k}$, the above performance index $J_c < 0$ under the constraint of Eq. (7).

2 Distributed H_∞ Fusion Filter Design

Considering each subsystem of Eq. (3) and applying Schur's complement theory and the discrete-time bounded real lemma[9], we obtain the following result in the INS/WSN integrated positioning system.

Theorem 1 If there exist feasible solutions $\tilde{\boldsymbol{P}} = \tilde{\boldsymbol{P}}^{\mathrm{T}} > 0$ to linear matrix inequality (9), the distributed H_∞ fusion filter is available for INS/WSN integrated positioning.

$$\begin{bmatrix} -\tilde{\boldsymbol{P}} & \mathbf{0} & \tilde{\boldsymbol{A}}^{\mathrm{T}}\tilde{\boldsymbol{P}} & \tilde{\boldsymbol{M}}^{\mathrm{T}} \\ \mathbf{0} & -\tilde{\gamma}^2\boldsymbol{I} & \tilde{\boldsymbol{K}}^{\mathrm{T}}\tilde{\boldsymbol{P}} & \mathbf{0} \\ \tilde{\boldsymbol{P}}\tilde{\boldsymbol{A}} & \tilde{\boldsymbol{P}}\tilde{\boldsymbol{K}} & -\tilde{\boldsymbol{P}} & \mathbf{0} \\ \tilde{\boldsymbol{M}} & \mathbf{0} & \mathbf{0} & -\boldsymbol{I} \end{bmatrix} < 0 \tag{9}$$

where

$$\tilde{\boldsymbol{A}} = \mathrm{diag}(\boldsymbol{A} - \boldsymbol{P}_1^{-1}\boldsymbol{Q}_1\boldsymbol{C}_1, \boldsymbol{A} - \boldsymbol{P}_2^{-1}\boldsymbol{Q}_2\boldsymbol{C}_2, \ldots, \boldsymbol{A} - \boldsymbol{P}_N^{-1}\boldsymbol{Q}_N\boldsymbol{C}_N)$$

$$\tilde{\boldsymbol{M}} = [\boldsymbol{M}_1, \boldsymbol{M}_2, \ldots, \boldsymbol{M}_N]$$

$$\tilde{\boldsymbol{K}} = \mathrm{diag}(\boldsymbol{B}_1 - \boldsymbol{P}_1^{-1}\boldsymbol{Q}_1\boldsymbol{D}_{11}, \boldsymbol{B}_1 - \boldsymbol{P}_2^{-1}\boldsymbol{Q}_2\boldsymbol{D}_{21}, \ldots, \boldsymbol{B}_1 - \boldsymbol{P}_N^{-1}\boldsymbol{Q}_N\boldsymbol{D}_{N1})$$

$$\tilde{\boldsymbol{P}} = \begin{bmatrix} \boldsymbol{P}_1 & \mathbf{0} & \ldots & \mathbf{0} \\ \mathbf{0} & \boldsymbol{P}_2 & \ldots & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \ldots & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \ldots & \boldsymbol{P}_N \end{bmatrix}$$

Here, $\boldsymbol{P}_c = \boldsymbol{P}_c^{\mathrm{T}} > 0$, $\boldsymbol{Q}_c\,(c = 1, 2, \ldots, N)$ are the feasible solutions to the following linear matrix inequality:

$$\begin{bmatrix} -\boldsymbol{P}_c & \mathbf{0} & \boldsymbol{A}^{\mathrm{T}}\boldsymbol{P}_c - \boldsymbol{C}_c^{\mathrm{T}}\boldsymbol{Q}_c^{\mathrm{T}} & \boldsymbol{L}_c^{\mathrm{T}} \\ \mathbf{0} & -\gamma_c^2\boldsymbol{I} & \boldsymbol{B}_1^{\mathrm{T}}\boldsymbol{P}_c - \boldsymbol{D}_{c1}^{\mathrm{T}}\boldsymbol{Q}_c^{\mathrm{T}} & \mathbf{0} \\ \boldsymbol{P}_c\boldsymbol{A} - \boldsymbol{Q}_c\boldsymbol{C}_c & \boldsymbol{P}_c\boldsymbol{B}_1 - \boldsymbol{Q}_c\boldsymbol{D}_{c1} & -\boldsymbol{P}_c & \mathbf{0} \\ \boldsymbol{L}_c & \mathbf{0} & \mathbf{0} & -\boldsymbol{I} \end{bmatrix} < 0 \tag{10}$$

Proof We first define

$$\tilde{\tilde{\boldsymbol{x}}}_k = [\tilde{\boldsymbol{x}}_{1,k}^{\mathrm{T}}, \tilde{\boldsymbol{x}}_{2,k}^{\mathrm{T}}, \ldots, \tilde{\boldsymbol{x}}_{N,k}^{\mathrm{T}}]^{\mathrm{T}} \tag{11}$$

$$\tilde{\boldsymbol{M}} = [\boldsymbol{M}_1, \boldsymbol{M}_2, \ldots, \boldsymbol{M}_N] \tag{12}$$

where $\tilde{\boldsymbol{x}}_{c,k}$, $\boldsymbol{M}_c\,(c = 1, 2, \ldots, N)$ are the same definitions as in Eq. (4) and Eq. (5). Combining the state error vector of each subsystem defined in Eq. (4), we can obtain

$$\tilde{\tilde{\boldsymbol{x}}}_{k+1} = \tilde{\boldsymbol{A}}\tilde{\tilde{\boldsymbol{x}}}_k + \tilde{\boldsymbol{K}}\tilde{\boldsymbol{\zeta}}_k,\ \ \tilde{\hat{\boldsymbol{x}}}_k = \tilde{\boldsymbol{M}}\tilde{\tilde{\boldsymbol{x}}}_k \tag{13}$$

where $\tilde{\boldsymbol{A}} = \mathrm{diag}(\boldsymbol{A} - \boldsymbol{K}_1\boldsymbol{C}_1, \boldsymbol{A} - \boldsymbol{K}_2\boldsymbol{C}_2, \ldots, \boldsymbol{A} - \boldsymbol{K}_N\boldsymbol{C}_p)$; $\tilde{\boldsymbol{K}} = \mathrm{diag}(\boldsymbol{B}_1 - \boldsymbol{K}_1\boldsymbol{D}_{11}, \boldsymbol{B}_1 - \boldsymbol{K}_2\boldsymbol{D}_{21}, \ldots, \boldsymbol{B}_1 - \boldsymbol{K}_N\boldsymbol{D}_{N1})$; and $\tilde{\boldsymbol{\zeta}}_k = [\boldsymbol{\zeta}_{1,k}^{\mathrm{T}}, \boldsymbol{\zeta}_{2,k}^{\mathrm{T}}, \ldots, \boldsymbol{\zeta}_{N,k}^{\mathrm{T}}]^{\mathrm{T}}$.

Here, we define the following performance index:

$$\tilde{J} = E\sum_{k=0}^{\infty}(\tilde{\hat{\boldsymbol{x}}}_k^{\mathrm{T}}\tilde{\hat{\boldsymbol{x}}}_k - \tilde{\gamma}^2\tilde{\boldsymbol{\zeta}}_k^{\mathrm{T}}\tilde{\boldsymbol{\zeta}}_k) \tag{14}$$

where $\tilde{\gamma} > 0$ is a given scalar. We seek an estimator from the system Eq. (13) such that for each nonzero $\tilde{\boldsymbol{\zeta}}_k$, the above performance index $\tilde{J} < 0$. In Eq. (13), $\boldsymbol{K}_c\,(c = 1, 2, \ldots, N)$ are unknown, and they are the parameters of the H_∞ filter to be designed for each cluster measurement system. Considering the system of Eq. (4) and applying the discrete-time bounded real lemma[9], given $\gamma_c > 0$, a necessary and sufficient condition for J_c in Eq. (8) is negative for all nonzero $\boldsymbol{\zeta}_k \in l_2[0, \infty)$. There exist feasible solutions $\boldsymbol{P}_c = \boldsymbol{P}_c^{\mathrm{T}} > 0, c = 1, 2, \ldots, N,$ to the following inequality:

$$-\boldsymbol{P}_c + \tilde{\boldsymbol{A}}_c^{\mathrm{T}}\boldsymbol{P}_c\tilde{\boldsymbol{A}}_c + \tilde{\boldsymbol{A}}_c^{\mathrm{T}}\boldsymbol{P}_c\tilde{\boldsymbol{B}}_c\tilde{\boldsymbol{\Theta}}_c^{-1}\tilde{\boldsymbol{B}}_c^{\mathrm{T}}\boldsymbol{P}_c\tilde{\boldsymbol{A}}_c + \boldsymbol{L}_c^{\mathrm{T}}\boldsymbol{L}_c < 0 \tag{15}$$

where $\boldsymbol{\Theta}_c > 0$ and $\boldsymbol{\Theta}_c = \gamma_c^2\boldsymbol{I} - \boldsymbol{B}_c^{\mathrm{T}}\boldsymbol{P}_c\boldsymbol{B}_c$. Applying Schur's complement theory to inequality (15), then it is equivalent to the linear matrix inequality (16).

$$\begin{bmatrix} -\boldsymbol{P}_c + \boldsymbol{L}_c^{\mathrm{T}}\boldsymbol{L}_c & \mathbf{0} & \tilde{\boldsymbol{A}}_c^{\mathrm{T}}\boldsymbol{P}_c \\ \mathbf{0} & -\gamma_c^2\boldsymbol{I} & \tilde{\boldsymbol{B}}_c^{\mathrm{T}}\boldsymbol{P}_c \\ \boldsymbol{P}_c\tilde{\boldsymbol{A}}_c & \boldsymbol{P}_c\tilde{\boldsymbol{B}}_c & -\boldsymbol{P}_c \end{bmatrix} < 0 \tag{16}$$

Then, substituting $\tilde{\boldsymbol{A}}_c$ and $\tilde{\boldsymbol{B}}_c$ into (16) and defining $\boldsymbol{Q}_c = \boldsymbol{P}_c\boldsymbol{K}_c$ and $\boldsymbol{K}_c = \boldsymbol{P}_c^{-1}\boldsymbol{Q}_c$, we can obtain the linear matrix inequality (10). So the proof is complete.

In Theorem 1, if we let $\gamma_c^2 = \bar{\gamma}_c$, $\tilde{\gamma}^2 = \bar{\gamma}$ and if the linear matrix inequalities (9) and (10) are linear with respect to $\{\boldsymbol{P}_c, \boldsymbol{Q}_c, \bar{\gamma}_c\}$ and $\{\tilde{\boldsymbol{P}}, \boldsymbol{M}_c, \bar{\gamma}\}$, we can obtain the optional H_∞ fusion filter by solving the optimization problem using the Matlab software.

3 Simulation and Performance Evaluation

All of the RNs are divided into three clusters in the simulation. The distance between the RNs is set to 7 m, and the communication range is set to 12 m. In the simulation, ultrasound-based wireless localization is used due to its high precision, and the accuracy of localization is assumed to be about 20 cm. As the WSN is a low speed wireless communication technology, we set the sampling time in Eq. (2) to be 0.02 s, and the mean and the standard deviation of system noise are set to be 6.5 and 1.2, respectively. For the INS, in all directions, we set the accelerometer bias to be 0.15 m/s^2; the accelerometer scale factor error is set to be 0.5%; and the accelerometer white noise standard deviation is set to be 0.017 m/s^2. According to Theorem 1, we obtain the following results.

Figs. 2(a) and (b) display the position errors for the INS-only, the federal Kalman and the proposed method in the x direction and the y direction, respectively. And the velocity errors for the INS-only, the federal Kalman and the proposed method in the x direction and the y direction are shown in Figs. 3(a) and (b), respectively. Simulation results show that the proposed method reduces the position errors in the x direction by about 80% compared with the INS only, and 50% compared with the federal Kalman solution. In the y direction, the position errors are reduced by about 85% compared with the INS only, and 40% compared with the federal Kalman solution. For the velocity errors, in the x direction, the proposed method

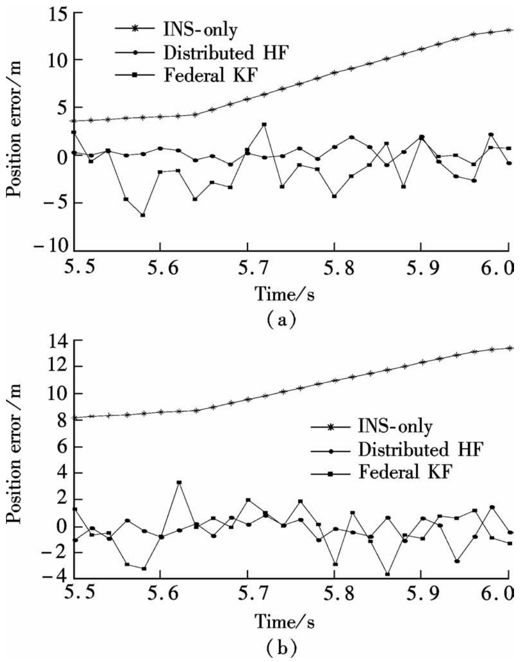

Fig. 2 The position errors. (a) x direction; (b) y direction

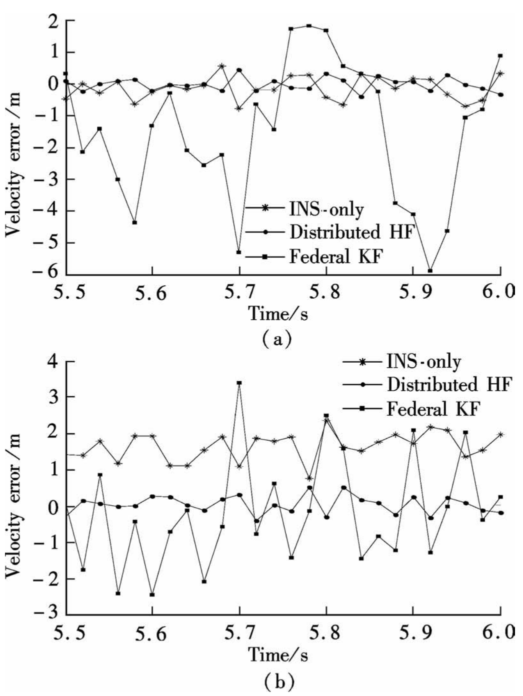

Fig. 3 The velocity errors. (a) x direction; (b) y direction

reduces the errors by about 40% compared with the INS only, and 90% compared with the federal Kalman solution; in the y direction, the proposed method reduces the errors by about 80% compared with the INS only, and 83% compared with the federal Kalman solution.

4 Conclusion

The distributed H_∞ fusion filter for WSN/INS integrated positioning is discussed. Applying H_∞ filtering theory and LMI methods, one theory and a design methods for the fusion filter are proposed. Simulation is used to evaluate the performance of the proposed method. The results show that both the federal Kalman solution and the proposed method solution can reduce the drifts of position errors and velocity errors for the INS. It can be seen that the proposed method is more effective than the federal Kalman solution. Obviously, it is very valuable in the study of distributed data information for the WSN/INS integrated positioning system, while many other problems merit further study.

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面向 INS/WSN 组合定位的分布式 H_∞ 融合滤波器设计

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摘要：为了保持未知节点在 2 个相邻簇之间移动时导航精度的稳定，提出了一种基于 H_∞ 滤波的惯性导航系统和无线传感器网络组合导航分布式融合方法. 由于组合系统的过程和测量噪声具有未知的但能量有界的统计特性，因此在提出的方法中，用 H_∞ 滤波器来融合局部估计测量的信息. 该滤波器能够根据一定的信息融合准则产生最佳的状态估计. 仿真结果显示：与联邦卡尔曼方法相比，提出的方法降低了 45% 的平均位置误差和 85% 的平均速度误差.

关键词：惯性导航系统；无线传感器网络；H_∞ 滤波器；分布融合

中图分类号：TN967.3