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Tightly-coupled model for INS/WSN integrated navigation based on Kalman filter

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Abstract: Aiming at the problem of poor observability of measurement information in the loosely-coupled integration of the inertial navigation system (INS) and the wireless sensor network (WSN), this paper presents a tightly-coupled integration based on the Kalman filter (KF). When the WSN is available, the difference between the distances from the blind node(BN) to the reference nodes (RNs) measured by the INS and those measured by the WSN are used as measurement information for the KF due to its better observability and independence, which can effectively improve the accuracy of the KF. Simulations show that the proposed approach reduces the mean error of the position by about 50% compared with loosely-coupled integration, while the mean error of the velocity is a little higher than that of loosely-coupled integration.

Key words: inertial navigation system(INS); wireless sensor network(WSN); tightly-coupled integration; Kalman filter
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How to provide a continuous navigation capability has been an important research issue in the past years[1-2]. In order to achieve continuous navigation capability, many approaches employ integrated navigation. The GPS/INS integration is one of the most common methods. However, although the global positioning systems (GPS) solution which has been in service for many years has a consistent and long-term stable accuracy, it cannot work when a total system outage occurs[3]. And in the GPS denied areas such as tunnels, urban canyons and indoors, the INS cannot provide long-term stable accuracy due to the accuracy deterioration with time.

With the development of the WSN in recent decades, it shows a great potential to develop indoor position systems in the GPS-denied area[4-8]. Most of the current localization means for wireless networks employ measurements of one or several physical parameters of the radio signal transmitted between the reference nodes (RNs) and the blind node (BN)[9]. For example, Patwari et al.[10] employed the time of arrival (TOA) and received signal strength (RSS) measurements to estimate the relative location in the wireless sensor networks (WSN). Minami et al.[11] proposed a fully distributed localization system based on ultrasound, and the accuracy of localization is about 20 cm. However, as the WSN requires high-density RNs to maintain localization accuracy, it has to employ a large number of RNs to maintain localization accuracy if the localization area is large.

As for data fusion, there are three integration modes: loosely, tightly and ultra-tightly coupled integration. Loosely coupled integration is a low-level integration and it is easy to realize, while the system accuracy is significantly affected by the environment. The advantages of the ultra-tightly coupled integrated system have already been presented in some literature, but it is not used in practice at present due to the limitations of receiver development[12].

In order to overcome the poor observability of measurement information in loosely-coupled integration and the limitation of device development in ultra-tightly coupled integration, this paper presents a tightly-coupled INS/WSN integrated navigation system for continuous navigation capability in the area of long-term GPS outage. Simulation results of the proposed method are used to evaluate the performance and are compared with those of the INS-only and loosely-coupled methods.

1 Principle of Tightly-Coupled INS/WSN Integration

1.1 Structure of integration

The structure of the tightly-coupled INS/WSN integration is shown in Fig. 1. The measurement information includes the BN velocity and the distances from the BN to the RNs. These measurements are used to generate estimates of the errors in the INS, and thus, the errors of measurement information are independent and not relevant.

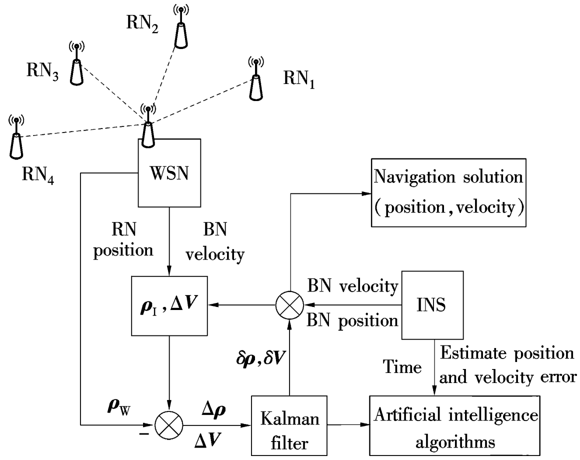

Fig. 1 The structure of integration when WSN is available

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From Fig. 1 it can be seen that the INS calculates the BN velocity and the distances from the BN to the RNs (denoted as $\boldsymbol{\rho}_{\mathrm{I}}$), and then compares them with those measured by the WSN. The integrated filter uses the comparison results to estimate the INS state errors, which are used to correct the navigation system.

1.2 State equation

As mentioned above, the measurement information of the INS includes $\boldsymbol{\rho}_{\mathrm{I}}$ and the BN velocity, therefore, the KF uses the errors of position and velocity of the BN as the state vector. The state equation of the INS error can be expressed as

$$\boldsymbol{X}_{\mathrm{I}}(k+1) = \boldsymbol{F}_{\mathrm{I}}\boldsymbol{X}_{\mathrm{I}}(k) + \boldsymbol{W}_{\mathrm{I}}(k) \tag{1}$$

where

$$\boldsymbol{X}_{\mathrm{I}}(k) = \begin{bmatrix} \delta\boldsymbol{P}_k \\ \delta\boldsymbol{V}_k \end{bmatrix}, \quad \boldsymbol{F}_{\mathrm{I}} = \begin{bmatrix} \boldsymbol{I} & \boldsymbol{T} \\ \boldsymbol{0} & \boldsymbol{I} \end{bmatrix}$$
$$\boldsymbol{T} = \begin{bmatrix} \Delta t & 0 \\ 0 & \Delta t \end{bmatrix}, \quad \boldsymbol{W}_{\mathrm{I}}(k) = \begin{bmatrix} \boldsymbol{\omega P}_k \\ \boldsymbol{\omega V}_k \end{bmatrix} \tag{2}$$

where $\delta\boldsymbol{P}$ and $\delta\boldsymbol{V}$ are the position and velocity errors, respectively; and Δt is the sampling period. The corresponding state equation of synchronization delay is

$$\delta_{\mathrm{d}}(k+1) = \delta_{\mathrm{d}}(k) + \omega_{\mathrm{d}}(k) \tag{3}$$

Combining the INS error state equation with the synchronization delay equation, the state equation in the mode of integration is achieved.

$$\underbrace{\begin{bmatrix} \boldsymbol{X}_{\mathrm{I}}(k+1) \\ \delta_{\mathrm{d}}(k+1) \end{bmatrix}}_{X(k+1)} = \underbrace{\begin{bmatrix} \boldsymbol{F}_{\mathrm{I}} & \boldsymbol{0} \\ 0 & 1 \end{bmatrix}}_{F} \underbrace{\begin{bmatrix} \boldsymbol{X}_{\mathrm{I}}(k) \\ \delta_{\mathrm{d}}(k) \end{bmatrix}}_{X(k)} + \underbrace{\begin{bmatrix} \boldsymbol{W}_{\mathrm{I}}(k) \\ \omega_{\mathrm{d}}(k) \end{bmatrix}}_{W(k)} \tag{4}$$

where $\boldsymbol{W}(k)$ is the Gaussian white noise with zero mean, and its covariance matrix is $\boldsymbol{Q}(k)$.

1.3 Measurement equation

In the integration of INS/WSN, the position of the BN measured by the INS is assumed as $(x_{\mathrm{I}}, y_{\mathrm{I}})$. ρ_{W} is the distance from the BN to the RNs measured by the WSN. Subsequently, the real-time ρ_{I} of the INS can be solved using the RN position (x_i, y_i) and $(x_{\mathrm{I}}, y_{\mathrm{I}})$ as follows:

$$\rho_{\mathrm{I}i} = ((x_{\mathrm{I}} - x_i)^2 + (y_{\mathrm{I}} - y_i)^2)^{1/2} \tag{5}$$

Then, Eq. (5) is used for the first-order Taylor expansion at the position $(x_{\mathrm{I}}, y_{\mathrm{I}})$ which is measured by the INS. So we obtain

$$\rho_{\mathrm{I}i} = ((x_{\mathrm{I}} - x_i)^2 + (y_{\mathrm{I}} - y_i)^2)^{1/2} + \frac{\partial\rho_{\mathrm{I}i}}{\partial x}\delta x + \frac{\partial\rho_{\mathrm{I}i}}{\partial y}\delta y \tag{6}$$

Meanwhile, the distances between the BN and the RNs measured by the WSN are

$$\rho_{\mathrm{W}i} = r_i + \delta_{\mathrm{d}} + \upsilon_{\rho_i} \tag{7}$$

where δ_{d} is the synchronization delay; r is the real distance from the BN to the RNs; and υ_ρ is the noise. Here, we define $\boldsymbol{\Delta\rho}$ as

$$\Delta\rho_i = \rho_{\mathrm{I}i} - \rho_{\mathrm{W}i} = \frac{\partial\rho_{\mathrm{I}i}}{\partial x}\delta x + \frac{\partial\rho_{\mathrm{I}i}}{\partial y}\delta y - \delta_{\mathrm{d}} - \upsilon_{\rho_i} \tag{8}$$

where

$$\frac{\partial\rho_{\mathrm{I}i}}{\partial x} = \frac{x - x_i}{\rho_{\mathrm{I}i}}, \quad \frac{\partial\rho_{\mathrm{I}i}}{\partial y} = \frac{y - y_i}{\rho_{\mathrm{I}i}} \tag{9}$$

Therefore, the measurement matrix can be expressed as

$$\boldsymbol{Z}(k) = \boldsymbol{H}(k)\boldsymbol{X}(k) + \boldsymbol{\eta}(k) \tag{10}$$

where

$$\boldsymbol{Z}(k) = \begin{bmatrix} \Delta\boldsymbol{V} \\ \boldsymbol{\Delta\rho} \end{bmatrix}, \quad \boldsymbol{H}(k) = \begin{bmatrix} \boldsymbol{0} \quad \boldsymbol{I}_{2\times 2} \quad \boldsymbol{0} \\ \hline \boldsymbol{P}_{n\times 5} \end{bmatrix}_{(n+2)\times 5}$$

$$\boldsymbol{\eta}(k) = \begin{bmatrix} \boldsymbol{\eta}_v \\ \boldsymbol{\eta}_\rho \end{bmatrix}, \quad \Delta\boldsymbol{V} = \begin{bmatrix} V_{x_{\mathrm{I}}} - V_{x_{\mathrm{W}}} \\ V_{y_{\mathrm{I}}} - V_{y_{\mathrm{W}}} \end{bmatrix}, \quad \boldsymbol{\Delta\rho} = \begin{bmatrix} \Delta\rho_1 \\ \vdots \\ \Delta\rho_n \end{bmatrix}$$

$$\boldsymbol{P} = \begin{bmatrix} \frac{\partial\rho_{\mathrm{I}1}}{\partial x} & \frac{\partial\rho_{\mathrm{I}1}}{\partial y} & 0 & 0 & -1 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \frac{\partial\rho_{\mathrm{I}n}}{\partial x} & \frac{\partial\rho_{\mathrm{I}n}}{\partial y} & 0 & 0 & -1 \end{bmatrix}$$

where $\boldsymbol{\eta}(k)$ is the Gaussian white noise with zero mean, and its covariance matrix is $\boldsymbol{R}(k)$. Here, we can readily see that the system composed of Eqs. (4) and (10) is a linear system. The KF is one of the most common filtering methods for linear systems, and the KF algorithm can be given in the following recursive relations:

$$\boldsymbol{X}(k) = \boldsymbol{X}(k-1) + \boldsymbol{K}(k)(\boldsymbol{Z}(k) - \boldsymbol{H}(k)\boldsymbol{X}(k-1)) \tag{11}$$

$$\boldsymbol{P}(k) = \boldsymbol{FP}(k-1)\boldsymbol{F}' + \boldsymbol{Q}(k) \tag{12}$$

$$\boldsymbol{K}(k) = \boldsymbol{P}(k-1)\boldsymbol{H}(k)'(\boldsymbol{H}(k)\boldsymbol{P}(k-1)\boldsymbol{H}(k)' + \boldsymbol{R}(k))^{-1} \tag{13}$$

$$\boldsymbol{P}(k) = (\boldsymbol{I} - \boldsymbol{K}(k)\boldsymbol{H}(k))\boldsymbol{P}(k) \tag{14}$$

2 Simulation and Performance Evaluation

2.1 Assumptions

In order to assess the performance of the proposed method, simulations are implemented. A 700 m × 400 m area is defined as the simulation scenario. We assume that the distance between RNs is 5 m, and the communication range is 15 m. As the WSN is low-speed wireless communication technology, we set the sampling period in Eq. (2) as 20 ms. In addition, the WSN employs ultrasound to measure the distances between the RNs and the BN, and the accuracy of ultrasound-based localization is assumed to be about 0.2 m. Both the synchronization delay and the delay of communication between nodes are set to 1 ns. For the INS, the position, velocity and corresponding error estimations are real-time data. In this paper, we employ the position and velocity errors as performance evaluation standards.

2.2 Performance analysis

To further clearly demonstrate how the proposed algorithm improves the accuracy of the solution, the position errors in x direction and y direction are shown in Fig. 2 (a) and Fig. 2 (b), respectively. From these figures we can see that both the loosely-coupled and tightly-coupled integration solutions can reduce the drift of the position errors, and the errors of the tightly-coupled solution are smaller than those of the loosely-coupled solution. Simulation results show that the proposed method is effective since it decreases the position errors in x direction and y direction by about 50%.

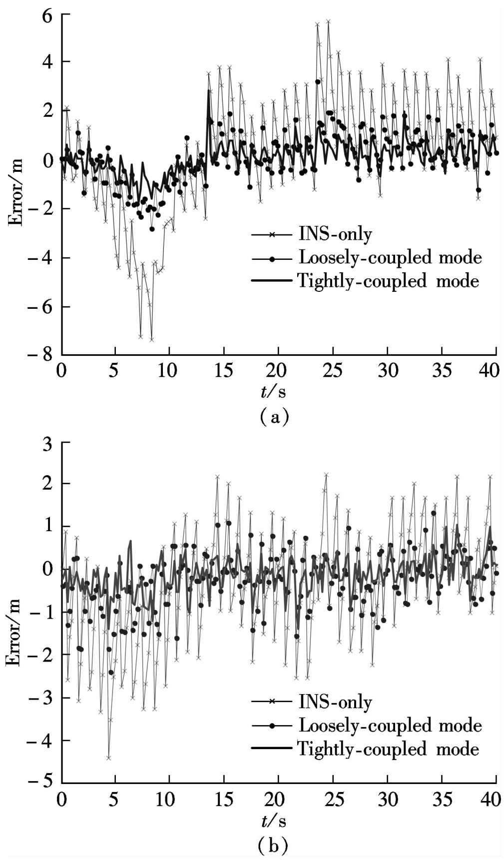

Fig. 2 Position errors for INS-only, loosely-coupled mode and tightly-coupled mode. (a) x direction; (b) y direction

Fig. 3 displays the velocity errors of the proposed method. It is evident that the proposed method has smaller velocity errors than the INS-only, although the velocity errors of the proposed method are a little higher than those of the loosely-coupled mode. Simulation results show that the proposed method is effective since it decreases the velocity by about 50% compared with the INS-only mode.

The mean errors of the position and the velocity are shown in Tab. 1.

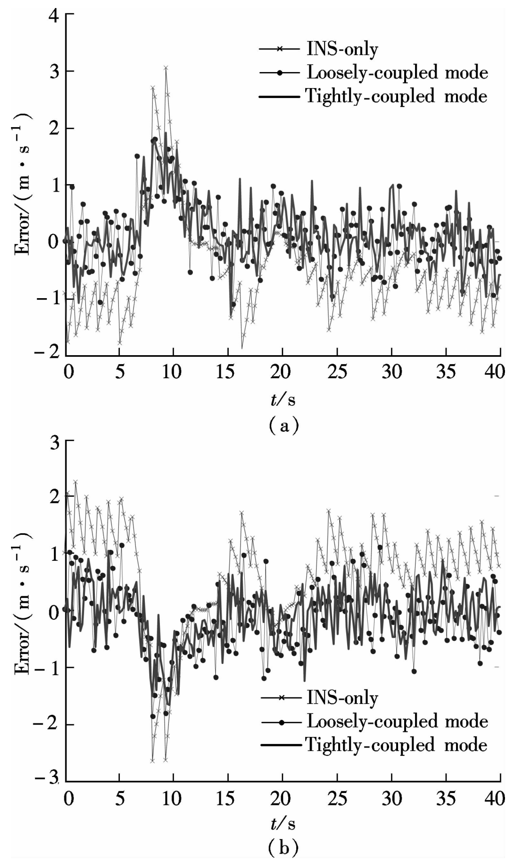

Fig. 3 Velocity errors for INS-only, loosely-coupled mode and tightly-coupled mode. (a) x direction; (b) y direction

Tab. 1 Performance of INS-only, loosely-coupled and tightly-coupled mode

Mode	Mean errors of the position/m		Mean errors of the velocity/($m \cdot s^{-1}$)	
	x direction	y direction	x direction	y direction
INS-only	1.779 2	1.191 9	0.829 8	0.843 5
Loosely-coupled integration	0.768 4	0.552 2	0.375 0	0.369 1
Tightly-coupled integration	0.419 2	0.299 7	0.362 1	0.377 4

3 Conclusion

This paper presents a tightly-coupled integrated navigation system with the Kalman filter based information fusion technology. In order to achieve better observability, the difference between the distances from the BN to the RNs measured by the INS and that measured by the WSN is used as measurement information of the KF for its better observability and independence, and the BN velocity is also used as measurement information in this mode. Simulation results show that the proposed approach effectively reduces the mean error of the position by about 50% compared with loosely-coupled integration, while the mean error of the velocity is a little higher than that of loosely-coupled integration. For the WSN, as the tightly-coupled integrated system employs the distances between RNs and BN instead of the position of the BN, the computation capacity requirements of the coordinator node in the proposed mode is reduced compared with that of the loosely-coupled mode.

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基于 Kalman 滤波器的 INS/WSN 紧组合导航系统模型

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摘要:在基于惯性导航系统和无线传感器网络的组合导航系统中,为了解决传统导航信息松组合方法中测量信息可观性较差的问题,提出了一种基于卡尔曼滤波器的导航信息紧组合模型. 当无线传感器网络的信号可用时,组合导航系统将惯性导航系统测量得到的未知节点与已知节点的距离与无线传感器网络测量得到的距离作差,差值作为卡尔曼滤波器的测量信息. 由于新测量信息具有更好的可观性和独立性,该方法有效地提高了卡尔曼滤波器的准确度. 仿真结果显示,提出的方法平均位置误差比松组合方法降低50% 左右,但平均速度误差却略高于松组合方式.

关键词:惯性导航系统;无线传感器网络;紧组合;卡尔曼滤波

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