General Solution for Asynchronous Sensors Bias Estimation

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Abstract - In multisensor systems, the measurements reported by local sensors are usually not time aligned or synchronous due to different data rates. A novel algorithm, based on Kalman filter combined with pseudomeasurement and equivalent bias, is proposed to solve a general bias estimate problem in asynchronous sensors systems. The pseudomeasurement equation of sensor biases is obtained by linearizing the last measurements provided by asynchronous sensors to remove the target state. The equivalent bias equation in each sampling interval of fusion center is derived from the bias dynamic equation of asynchronous sensors with different rates. Monte Carlo simulation results show that the Cramer-Rao lower bound (CRLB) is achievable, i.e., the new algorithm is statistically efficient.

Keywords: Asynchronous sensors, bias estimate, pseudomeasurement, equivalent bias, Kalman filter.

1 Introduction

In multiplatform multisensor systems, information fusion can improve detection probability and increase system reliability. However, direct information fusion usually yields inaccurately the state estimation due to the sensor biases. Sensor registration is an inherent problem in multisensor information fusion and deals with the calibration of registration biases [1]. Accurate registration is a prerequisite for multisensor information fusion. If uncorrected, registration biases can seriously degrade the system performance due to the introduction tracking errors, and large errors will generate ghost targets for multisensor signal processing [2].

On-line bias estimate methods have been researched by many scholars. The conventional approach is to implement the augmented state Kalman filter (ASKF) by stacking the state of all the targets and sensor bias into a single vector, but this method can be computationally infeasible. In [3], the extended Kalman filter (EKF) method was presented to estimate the target state, position, and orientation bias, using a nonlinear coordinated turn maneuver model. In [4], the authors proposed the unscented Kalman filter (UKF) method to estimate the sensor biases and vehicle state simultaneously, using augmented state and measurement equations. In [5], Lin, Bar-shalom, and Kirubarajan presented the “exact” (EX) method in the minimum mean square sense to handle the dynamic sensor bias estimation based on multiple targets and multiple frames.

All of these previous papers on sensor registration are considering only synchronous sensors. However, in reality, the target data reported by asynchronous sensors is usually not time aligned or synchronous due to different data rates. The calibration of asynchronous sensors does not seem to be widely recognized [6]. Lin, et al [6] extended the work of [5] to asynchronous sensors and transformed the measurements from the different times of the sensors into pseudomeasurements in a “proper time slots”. The “proper time slots” has a restrictive assumption that the first \( n \) measurements must be from one sensor, and the last measurement must be from the other sensor. In [7], Rafati extends the work of [6] with the assumption that the present measurement must be fused with the last previous measurements from both sensors. However, all of these registration algorithms for asynchronous sensors have the following three limitations: 1) they can estimate the biases of asynchronous sensors only for a pair of sensors; 2) the measurements from asynchronous sensors must be in strict sequence, i.e., the data rates of asynchronous sensors are not arbitrary; and 3) the effect of autocorrelated measurement noises in the pseudomeasurement equation is not considered, which degenerates the performance of bias estimate.

This paper extends the work of [6] and [7], and the objective of the work is to present a general asynchronous sensor bias estimation algorithm that is directly applicable to the asynchronous sensors systems with arbitrary data rates, which is more realistic and practicable in multisensor systems.

This work is organized as follows. Section 2 formulates the asynchronous sensors fusion problem. Section 3 discusses the biased measurement model for asynchronous sensors. Dynamic bias estimator based on Kalman filter is presented in Section 4. Section 5 shows the simulation results of the bias estimation in asynchronous sensors. Section 6 concludes the work.
2 Asynchronous sensors fusion problem

Consider a linear dynamical system with the state equation

$$\dot{X}(t) = AX(t) + u(t)$$  \hspace{1cm} (1)

where \( A \) is the system matrix; \( X(t) \) is the continuous time system state at time \( t \), and the state vector is defined as \( X(t) = [x(t), \dot{x}(t), y(t), \dot{y}(t)]' \); \( u(t) \) is zero mean, white Gaussian process noise with covariance

$$E[u(t)u(t)'] = q(t)$$  \hspace{1cm} (2)

where ' denotes transpose, and \( q(t) \) is the continuous time process noise intensity which is its power spectral density. Assume that 1) no communication delays exist between local sensors and fusion center; 2) the system state is observed by \( m \) \((m \geq 2)\) sensors that have different data rates; 3) there is at least one measurement from local sensor \( i \) \((i=1,\ldots,m)\); 4) there have been \( N_k \) measurements obtained by the \( m \) sensors during time interval \((t_{k-1}, t_k] \) of the fusion center. Let \( n^i_k \) be the number of measurements provided by local sensor \( i \) during the given time interval. Then we have [8]

$$N_k = \sum_{i=1}^{m} n^i_k, \quad (n^i_k \geq 1, k \geq 1)$$  \hspace{1cm} (3)

In the time interval \((t_{k-1}, t_k] \), all the measurements from these \( m \) sensors are sent to the fusion center. Let \( z^i_{k,j} \) and \( z^i_{k,f} \) be the \( n^i_k \)th measurement (or the last measurement) reported by sensor \( i \) and the \( j \)th measurement \((j = 1, 2, \ldots, N_k) \) received by the fusion center during the time interval, respectively. Then the fusion center orders these measurements in sequence according to the "timestamp" [8] sign of measurements as \( z^i_{k,f}, z^i_{k,f}, \ldots, z^i_{k,f} \) shown in Figure 1.

Let \( T = t_k - t_{k-1} \) be the sampling period of the fusion center, and let \( T_i \) and \( k_i \) be the sampling period and the sampling number of sensor \( i \), respectively. We have

$$k_i = k_i T_i, \quad (T_i \leq T)$$  \hspace{1cm} (4)

$$k_i = \text{floor}((k-1)T/T_i), \quad (1 \leq l_i \leq n^i_k)$$  \hspace{1cm} (5)

where \( t_{k_i} \in (t_{k-1}, t_k] \), and \((k-1)\) is the sampling number of sensor \( i \) in time interval \((0, t_{k-1}] \).

$$\overline{(k-1)} = \text{floor}[(k-1)T/T_i] = \sum_{g=1}^{l_i} n^i_g, \quad (n^i_0 = 0)$$  \hspace{1cm} (6)

where \text{floor}() rounds the elements of ( ) to the nearest integers towards minus infinity. From (5) and (6), we have

$$\bar{r}^i = (k-1)_l + n^i_g$$  \hspace{1cm} (7)

where \( \bar{r}^i \) is the sampling number of sensor \( i \) during the time interval.

3 Biased measurement model for asynchronous sensors

The model for the biased measurements in polar coordinates for sensor \( i \) at time \( t_{k_i} \) is

$$\begin{bmatrix} r^i(t_{k_i}) \\ \theta^i(t_{k_i}) \end{bmatrix} = \begin{bmatrix} 1 + e^i_r(t_{k_i}) & 0 \\ 0 & 1 + e^i_{\theta}(t_{k_i}) \end{bmatrix} \begin{bmatrix} r(t_{k_i}) \\ \theta(t_{k_i}) \end{bmatrix} + \begin{bmatrix} b^i_r(t_{k_i}) \\ b^i_{\theta}(t_{k_i}) \end{bmatrix} + \begin{bmatrix} v^i_r(t_{k_i}) \\ v^i_{\theta}(t_{k_i}) \end{bmatrix}$$  \hspace{1cm} (8)

where \( r^i(t_{k_i}) \) and \( \theta^i(t_{k_i}) \) are the biased measurements of range and azimuth; \( r(t_{k_i}) \) and \( \theta(t_{k_i}) \) are the true range and azimuth; \( e^i_r(t_{k_i}) \) and \( e^i_{\theta}(t_{k_i}) \) are the scale biases of the range and azimuth; \( b^i_r(t_{k_i}) \) and \( b^i_{\theta}(t_{k_i}) \) are the offset biases of the range and azimuth; the measurement noises \( v^i_r(t_{k_i}) \) and \( v^i_{\theta}(t_{k_i}) \) are zero mean, white with corresponding variances \((\sigma^i_r)^2\) and \((\sigma^i_{\theta})^2\), respectively; and the measurement noises are assumed mutually independent from sensor to sensor.

Note that the state equation (1) is linear in the Cartesian coordinates while the measurement is nonlinear function of the target state in polar coordinates. In such case, the measurement model in the Cartesian coordinates can be obtained by linearization around the state estimate [9].

After transforming the measurements in polar coordinates into the measurements in Cartesian coordinates, we have the measurement equation for sensor \( i \) at time \( t_{k_i} \)

$$z(t_{k_i}) = HX(t_{k_i}) + B_i(t_{k_i})C_i(t_{k_i})\beta_i(t_{k_i}) + V_i(t_{k_i})$$  \hspace{1cm} (9)

where

$$X(t_{k_i}) = \Phi(t_{k_i}, t_{k_i-1})X(t_{k_i-1}) + U^i_{k_i}$$  \hspace{1cm} (10)
\[ \Phi(t_k, t_{k-1}) = e^{A(t_k - t_{k-1})} \] 
\[ U_{q_{k-1}}^{t_k} = \int_{t_{k-1}}^{t_k} \Phi(t_k, \tau)u(\tau)d\tau \] 
\[ E[U_{q_{k-1}}^{t_k} U_{q_{k-1}}^{t_k}] = O_{q_{k-1}}^{t_k} \]

where the state vector is rewritten as 
\[ X(t_k) = [x(t_k), \dot{x}(t_k), y(t_k), \dot{y}(t_k)]', \] 
and the measurement matrix \( H \) is defined as 
\[ H \triangleq \begin{bmatrix} 1 & 0 & 0 & 0 \end{bmatrix} \] 

The matrices \( B_i(t_k), C_i(t_k) \) and \( \beta_i(t_k) \) are given by 
\[ B_i(t_k) = \begin{bmatrix} \cos \theta^p_i(t_k) & -r^p_i(t_k) \sin \theta^p_i(t_k) \\ \sin \theta^p_i(t_k) & r^p_i(t_k) \cos \theta^p_i(t_k) \end{bmatrix} \]
\[ C_i(t_k) = \begin{bmatrix} 1 & 0 & r_i(t_k) & 0 \\ 0 & 1 & \theta(t_k) & 0 \end{bmatrix} \]
\[ \beta_i(t_k) = \begin{bmatrix} b_i(t_k) & b_i^o(t_k) & e_i(t_k) & e_i^o(t_k) \end{bmatrix} \]

The measurement noise \( V_i(t_k) \) in the Cartesian coordinates is zero mean, white with covariance \([10]\)
\[ E[V_i(t_k) V_i(t_k)'] = R_i(t_k) = \begin{bmatrix} R_i(t_k, 11) & R_i(t_k, 12) \\ R_i(t_k, 21) & R_i(t_k, 22) \end{bmatrix} \]

where
\[ R_i(t_k, 11) = [r_i^p(t_k)]^2 (\sigma_{\theta_i})^2 \{\sin[\theta_i^p(t_k)]\}^2 \]
\[ + (\sigma_{\theta_i})^2 \{\cos[\theta_i^p(t_k)]\}^2 \]
\[ R_i(t_k, 12) = R_i(t_k, 21) = [\{\sigma_{\theta_i}\}^2 - [r_i^p(t_k)]^2 \]
\[ \times \{\sin[\theta_i^p(t_k)]\} \cos[\theta_i^p(t_k)] \}
\[ R_i(t_k, 22) = [r_i^p(t_k)]^2 (\sigma_{\theta_i})^2 \{\cos[\theta_i^p(t_k)]\}^2 \]
\[ + (\sigma_{\theta_i})^2 \{\sin[\theta_i^p(t_k)]\}^2 \]

4 Dynamic bias estimation

4.1 Dynamic stochastic process model for sensor biases

The dynamic equation of bias vector for sensor \( i \) is 
\[ \beta_i(t_k) = F_i \beta_i(t_{k-1}) + v_i(t_{k-1}) \] 
where \( F_i \) is the transition matrix of the bias vector \( \beta_i(t_{k-1}) \); and the process noise \( v_i(t_{k-1}) \) is zero mean, white with covariance \( R_i \), and they are mutually independent from sensor to sensor. Time invariant constant bias is an especial case of dynamic bias when \( F_i = I, v_i(t_{k-1}) = 0 \).

4.2 Pseudomeasurement of sensor biases

Assume that the last measurement from local sensor \( i \) at \( t_{k_i} \) is known. Without loss of generality, we assume that these asynchronous measurements from \( m \) sensors are \( z_1(t_{k_1}), z_2(t_{k_2}), \ldots, z_m(t_{k_m}) \) with \( t_{k_1} < t_{k_2} < \ldots < t_{k_m} \). It can be easily extended to the case when the time indices are not in the above relationship, and similar results can be obtained. Below we construct a pseudomeasurement equation of sensor biases based on the last measurements from these \( m \) sensors. The asynchronous measurements can be expressed by using the true target state at time index \( t_{k_i} \). From (9) and (10), we have
\[ z_i(t_{k_i}) = HX(t_{k_i}) + B_i(t_{k_i})C_i(t_{k_i})\beta_i(t_{k_i}) + V_i(t_{k_i}) \]
\[ = H\Phi(t_{k_i}, t_{k_i})X(t_{k_i}) + HU_{\tau_{k_i}}^{t_{k_i}} + B_i(t_{k_i})C_i(t_{k_i})\beta_i(t_{k_i}) + V_i(t_{k_i}) \]
\[ + V_i(t_{k_i}) \]

A linear function of these \( m \) asynchronous measurements is defined as
\[ Z_m(t_{k_1}, \ldots, t_{k_m}) \]
\[ \triangleq z_m(t_{k_m}) - [L_{m-1}(t_{k_m}) z_{m-1}(t_{k_m-1}) + \ldots + L_1(t_{k_m}) z_1(t_{k_1})] \]
\[ = [H\Phi(t_{k_m}, t_{k_m}) - L_{m-1}(t_{k_m}) H\Phi(t_{k_m}, t_{k_m-1}) + \ldots + L_1(t_{k_m}) H \]
\[ \times \Phi(t_{k_m}, t_{k_m})] X(t_{k_m}) + [B_m(t_{k_m}) C_m(t_{k_m}) \beta_m(t_{k_m}) \]
\[ - [L_{m-1}(t_{k_m}) B_{m-1}(t_{k_m}) C_{m-1}(t_{k_m}) \beta_{m-1}(t_{k_m}) + \ldots \]
\[ + L_1(t_{k_m}) B_1(t_{k_m}) C_1(t_{k_m}) \beta_1(t_{k_m})] + HU_{\tau_{k_m}}^{t_{k_m}} \]
\[ - [L_{m-1}(t_{k_m}) U_{\tau_{k_m}}^{t_{k_m-1}} + \ldots + L_1(t_{k_m}) U_{\tau_{k_m}}^{t_{k_m-1}}] V_m(t_{k_m}) \]
\[ - [L_{m-1}(t_{k_m}) V_{(m-1)}(t_{k_m-1}) + \ldots + L_1(t_{k_m}) V_{(m-1)}(t_{k_m-1})] \]

To cancel the first term on the right of (25), we have
\[ H\Phi(t_{k_m}, t_{k_m}) - [L_{m-1}(t_{k_m}) t_{k_m-1}) + \ldots + L_1(t_{k_m}) t_{k_m-1})] = 0 \]

where \( L_i(t_{k_i}) \) is the weighting coefficient of the measurements.

When the first term on the right of (25) is zero, the pseudomeasurement equation of sensor biases is expressed as
\[ Z_m(t_{k_1}, \ldots, t_{k_m}) \]
\[ \triangleq \Psi(\kappa) \beta(\kappa) + \delta(\kappa) \]

where
\[ \beta(\kappa) \triangleq [\beta_i(t_{k_1})', \ldots, \beta_i(t_{k_m})']' \]
\[ \Psi(\kappa) \triangleq \Gamma(t_{k_1}, \ldots, t_{k_m}) \Xi(t_{k_1}, \ldots, t_{k_m}) \]
\[ \delta(\kappa) \triangleq \Gamma(t_{k_1}, \ldots, t_{k_m}) \mathcal{A}(t_{k_1}, \ldots, t_{k_m}) \Xi(t_{k_1}, \ldots, t_{k_m}) + \mathcal{R}(t_{k_1}, \ldots, t_{k_m}) \]
\[\Gamma(t_{\tau_1}, ..., t_{\tau_n}) \triangleq \left[ -L_1(t_{\tau_1}), ..., -L_{m-1}(t_{\tau_n}) \right] \]
\[C(t_{\tau_1}, ..., t_{\tau_n}) \triangleq \text{diag}[B_1(t_{\tau_1})C_1(t_{\tau_1}), ..., B_m(t_{\tau_n})C_m(t_{\tau_n})] \]
\[\Lambda(t_{\tau_1}, ..., t_{\tau_n}) \triangleq \text{diag}[H_{\tau}, ..., H_{\tau}] \]
\[Q(t_{\tau_1}, ..., t_{\tau_n}) \triangleq \left[ U_{\tau_1}^{-1}, ..., U_{\tau_n}^{-1} \right]' \]
\[\Re(t_{\tau_1}, ..., t_{\tau_n}) \triangleq \left[ V_{\tau_1}^{-1}, ..., V_{\tau_n}^{-1} \right]' \]

Inserting (38) - (41) into (28), we have the equivalent bias equation for asynchronous sensors
\[\hat{b}(\kappa + 1) = F_h(\kappa)\hat{b}(\kappa) + w_h(\kappa) \]

where
\[F_h(\kappa) = \text{diag}[(F_{h_1})^{n_{h_1}}, ..., (F_{h_n})^{n_{h_n}}] \]
\[w_h(\kappa) = \left[ w_{h_1}, ..., w_{h_n} \right]' \]

where the noise \( w_{h_i}(\kappa) \) is zero mean, white with covariance
\[W_h(\kappa) = E[w_h(\kappa)w_h(\kappa)'] = \text{diag}[W_{h_1}, ..., W_{h_n}] \]

\[4.4 \text{ Bias estimator based on Kalman filter} \]
Asume the bias vector estimate \( \hat{b}(\kappa|\kappa) \) and bias covariance \( P(\kappa|\kappa) \) are available. From (27) and (43), the bias estimator based on Kalman filter is given by
\[\hat{b}(\kappa + 1|\kappa + 1) = \hat{b}(\kappa + 1|\kappa) + G(\kappa + 1)[Z(\kappa + 1) - \hat{Z}(\kappa + 1)] \]

\[4.3 \text{ Equivalent bias} \]
From the dynamic bias equation (23), we have
\[\beta_i(t_{\tau_i}) = F_h(\kappa)\beta_i(t_{\tau_i}) + v_i(t_{\tau_i}) \]
\[F_h(\kappa)[F_h(\kappa)\beta_i(t_{\tau_i}) + v_i(t_{\tau_i})] + v_i(t_{\tau_i}) \]
\[F_h(\kappa)\beta_i(t_{\tau_i}) + F_h(\kappa)v_i(t_{\tau_i}) + v_i(t_{\tau_i}) \]
\[F_h(\kappa)^{n_{h_i}}\beta_i(t_{\tau_i}) + F_h(\kappa)^{n_{h_i}}v_i(t_{\tau_i}) + v_i(t_{\tau_i}) \]

\[4.5 \text{ Dynamic bias estimation of three asynchronous sensors} \]
Consider a scenario with three asynchronous sensors \((n=3)\) with different sampling rates in a 500s time interval. Sensors 1, 2, and 3 report measurements at 1.1s, 1.9s, and 4.1s interval, respectively. Assume that fusion center receives measurements at \(T=5\)s interval. The sensors are located at \((0,0)\), \((100,0)\), and \((50,100)\) in kilometers, respectively. The geometry of the targets and sensors is shown in Figure 2, and the targets are moving at nearly constant velocity with \(\dot{x} = \dot{y} = 20 \text{ m/s}\).
The dynamic equation of the target is modeled as a discretized continuous white noise acceleration (DCWNA) model [11]. The transition matrix of the target state between time $t_a$ and $t_d$ is given by

$$
\Phi(t_a, t_d) = e^{A(t_a-t_d)} = \begin{bmatrix}
1 & t_a - t_d & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & t_a - t_d \\
0 & 0 & 0 & 1
\end{bmatrix}
$$

(54)

From (26) and (54), we have

$$
L_x(t_{x_i}) = (t_{x_i} - t_{x_i})/(1 + t_{x_i} - t_{x_i})
$$

(55)

$$
L_x(t_{x_i}) = (1 + t_{x_i} - t_{x_i})/((1 + t_{x_i} - t_{x_i})
$$

(56)

The process noise covariance between time $t_a$ and $t_d$ is

$$
Q_{x_a} = \begin{bmatrix}
Q(x)^{x_a} & 0 \\
0 & Q(y)^{x_a}
\end{bmatrix}
$$

(57)

$$
Q(x)^{x_a} = Q(y)^{x_a} = \begin{bmatrix}
\frac{1}{3} (t_a - t_d)^3 & \frac{1}{2} (t_a - t_d)^2 \\
\frac{1}{2} (t_a - t_d)^2 & (t_a - t_d)
\end{bmatrix}
\tilde{q}
$$

(58)

where the power spectral densities is $\tilde{q} = 6 \text{m}^2 / s^3$.

The standard deviation of the measurement noise variances are $\sigma_{x_i} = 10m$ and $\sigma_{\theta_i} = 1\text{mrad}$ for the range and the azimuth measurements, respectively. The sensor biases are modeled as the dynamic stochastic process (23). The initial bias of sensor $i$ in the simulation is $\beta_i = [20m, 2\text{mrad}, 3 \times 10^{-5}, 2 \times 10^{-4}]'$. The transition matrices of biases are $F_{b_i} = 0.999$, $F_{b_i} = 0.998$, and $F_{b_i} = 0.996$, respectively. The covariance of process noise is $R_b = [(2m)^2, (0.3\text{mrad})^2, (0.4 \times 10^{-5})^2, (2 \times 10^{-5})^2]$. The initial estimate of equivalent bias is zero mean with covariance $P(0|0) = \text{diag} [P_x(0), P_y(0), P_z(0)]$, and $P(0) = \text{diag} [(100m)^2, (30\text{mrad})^2, (5 \times 10^{-3})^2, (2 \times 10^{-3})^2]$. The simulation results are based on 100 Monte Carlo runs. The Cramer-Rao lower bound (CRLB) is given by the covariance (50) [11]. Figures 3-6 show that the curves of the root mean square (RMS) errors are close to the curves of the CRLB. The range and azimuth offset bias RMS
errors are shown in Figures 3 and 4, and the range and azimuth scale bias RMS errors are shown in Figures 5 and 6. The CRLB of sensor 1 is only given in Figures 3-6, since the CRLBs of the three sensors are almost same. The biases are dynamic in each sampling for local sensor, and the bias estimator is based on the equivalent equation (43). Therefore, Figures 3-6 show the bias RMS estimation errors 100 times as many as the sampling times of the fusion center.

5.2 Comparison between two methods

Consider another scenario with two asynchronous sensors ($m=2$) with different sampling rates in a 66s time interval. Sensors 1 and 2 report measurements at 1s and 3s interval, respectively. Two sensors are located at $(0, 0)$ and $(100, 0)$ in kilometers, respectively. Assume that fusion center receives measurements at $T=3s$ interval, and there is 2.5s time offset between the initial reporting times of the two sensors. The transition matrix of dynamic biases is $F_n = 0.992$. The other parameters are the same as the previous example.

The simulation results with 100 Monte Carlo runs show the comparisons between the new method and other method [6] in Figures 7-10. The range and azimuth offset bias RMS errors comparisons between the two methods are shown in Figures 7 and 8, and the range and azimuth scale bias RMS errors comparisons are shown in Figures 9 and 10. The performances of the proposed method have significant improvement in Figures 7-10.
Though the new method has less measurements than the current method in a given time interval, it has better performance. The reasons are 1) the bias estimator based on Kalman filter is implemented in a “linear” system where the pseudomeasurement bias equation and the equivalent bias equation are linear functions for sensor biases; 2) the autocorrelated measurement noises are not introduced in the pseudomeasurement equation.

6 Conclusion

This work presents a novel solution for general dynamic bias estimation problem in asynchronous sensors systems. Bias estimate and target state estimate are independent processes, and there are not approximations for bias estimation. The new algorithm based on kalman filter is implemented recursively. The simulation results show that the proposed algorithm is statistically efficient to estimate the dynamic bias in asynchronous sensors systems.

The main advantages and features of the algorithm are summarized as follows: 1) It works with arbitrary number of asynchronous sensors; 2) Asynchronous sensors with arbitrary communication rates can be registered; 3) the effect of autocorrelated measurement noises in the pseudomeasurement equation is considered, and the autocorrelated measurement noises are not introduced in the pseudomeasurement equation which is a linear function of the measurements from different local sensors; and 4) the proposed method has less computation since less measurements are used in the pseudomeasurement equation. The algorithm can be used to register asynchronous sensors in practical systems, and it is also adapted for both time invariant biases and synchronous sensors biases with similar results.

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References


