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# Unscented Kalman Filtering for Hybrid Estimation of Spacecraft Attitude Dynamics and Rate Sensor Alignment

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## 1. Introduction

Requirements of highly precise pointing performance have been imposed on recently developed spacecrafts for a variety of missions. The stringent requirements have called on on-orbit estimation of spacecraft dynamics parameters and calibration of on-board sensors as indispensable practices.

Consequently, on-orbit estimation of the mass moment of inertia of spacecraft has been a major issue mostly due to the changes by solar panel deployment and a large portion of fuel consumption (Creamer et al., 1996; Ahmed et al., 1998; Bordany et al., 2000; VanDyke et al., 2004; Myung et al., 2007; Myung & Bang, 2008; Sekhavat et al., 2009).

As for measurement sensors, on-board calibration of alignment and bias errors of attitude and rate sensors is one of the main concerns of attitude sensor calibration researches (Pittelkau, 2001 & 2002, Lai et al., 2003). Pittelkau (2002) proposed an attitude estimator based on the Kalman filter (Kalman, 1960), in which spacecraft attitude quaternion, rate sensor misalignment and bias, and star tracker misalignments are taken into consideration as states, whereas the body rate is dealt as a synthesized signal by the estimates. Lai et al. (2003) derived a method for alignment estimation of attitude and rate sensors based on the unscented Kalman filter (UKF) (Julier and Uhlmann, 1997). Ma and Jiang (2005) presented spacecraft attitude estimation and calibration based only magnetometer measurements using an UKF.

An interesting point is that we need predesigned 3-axis excitation manoeuvres of spacecraft for both dynamics parameter estimation and sensor calibration. Therefore, this study is motivated to merge above estimation and calibration processes into a single filtering problem. It is noteworthy that poor information of moments of inertia is to be treated as a system uncertainty while the rate sensor model errors are to be incorporated into the measurement process.

As a filtering algorithm, this study employs a UKF. Extended Kalman filters (EKF) have been successfully applied to the nonlinear attitude estimation problem (Crassidis et al., 2007). Hybrid estimation using the EKF has been reported by Myung et al. (2007). However, the EKF estimates using the first order linearization, which may lead to instability of the filter (VanDyke et al., 2004). The UKF approximates the nonlinear model to the second order by spreading points 1 sigma apart from the *a priori* mean. Performing nonlinear

transformation of sigma points produces the *posterior* mean and covariance. Despite the computational burden of the UKF, extension of convergence region and numerical stability greatly outperform the EKF.

Parameter estimation by a dual UKF was proposed by VanDyke et al. (2004). Since UKF has more computational burden compared to EKF, a numerically efficient UKF was also developed for state and parameter estimation (van der Merwe & Wan, 2001).

In this paper, the UKF is applied to simultaneous spacecraft dynamics estimation and rate sensor alignment calibration using star tracker measurements. The spacecraft attitude and the body angular velocity are the state vectors. Estimation parameters are the six components of moment of inertia, and the bias, scale factor errors and misalignments of a rate sensor. Numerical simulations compare the results to those using the EKF.

## 2. Equation of motion of spacecraft

### 2.1 Attitude representation

Spacecraft attitude parameter is the unit quaternion defined by

$$\begin{aligned} \mathbf{q} &= \left[ \mathbf{n}^T \sin\left(\frac{\phi}{2}\right) \quad \cos\left(\frac{\phi}{2}\right) \right]^T \\ &= [q_1 \quad q_2 \quad q_3 \quad q_4]^T \\ &= [q_{13} \quad q_4]^T \end{aligned} \quad (1)$$

where  $\mathbf{n}$  is the Euler axis and  $\phi$  is the Euler angle.  $q_{13}$  is the vector part and  $q_4$  is the scalar part in quaternion representation. Quaternion multiplication represents successive rotation (Wertz, 1978)

$$\begin{aligned} \mathbf{q}'' &= \mathbf{q}' \otimes \mathbf{q} \\ &= \begin{bmatrix} q'_4 & q'_3 & -q'_2 & q'_1 \\ -q'_3 & q'_4 & q'_1 & q'_2 \\ q'_2 & -q'_1 & q'_4 & q'_3 \\ -q'_1 & -q'_2 & -q'_3 & q'_4 \end{bmatrix} \begin{bmatrix} q_1 \\ q_2 \\ q_3 \\ q_4 \end{bmatrix} \end{aligned} \quad (2)$$

And inverse of quaternion

$$\mathbf{q}^{-1} = [-q_1 \quad -q_2 \quad -q_3 \quad q_4]^T \quad (3)$$

implies the opposite rotation of  $\mathbf{q}$ . By combining Eq. (2) and (3) residual rotation of  $\mathbf{q}''$  with respect to  $\mathbf{q}'$ , or error quaternion  $\delta\mathbf{q}$ , is obtained such as

$$\delta\mathbf{q} = \mathbf{q}'' \otimes (\mathbf{q}')^{-1} \quad (4)$$

### 2.2 Spacecraft attitude equation of motion

The equation of motion of spacecraft is given as

$$\mathbf{J}\dot{\boldsymbol{\omega}} + \boldsymbol{\omega} \times \mathbf{J}\boldsymbol{\omega} = \mathbf{u} \quad (5)$$

where  $\omega \in R^3$  is the body angular velocity,  $J$  is the mass moment of inertia matrix, and  $u \in R^3$  is the external control input torque. The attitude kinematics is expressed by attitude quaternion such as (Crassidis et al., 1997)

$$\dot{q} = \frac{1}{2}\Omega(\omega)q = \frac{1}{2}\Xi(q)\omega \tag{6}$$

where

$$\Omega(\omega) \equiv \left[ \begin{array}{c|c} -[\omega \times] & \omega \\ \hline -\omega^T & 0 \end{array} \right], \Xi(q) \equiv \left[ \begin{array}{c} q_4 I_3 + [q_{13} \times] \\ \hline -q_{13}^T \end{array} \right] \tag{7}$$

Due to the unity constraint on the attitude quaternion, only the vector component is utilized as states, and  $q_4$  is calculated from the constraint. Choosing the body angular rate as one of the states, we rewrite Eq. (5) as

$$\dot{\omega} = -J^{-1}\omega \times J\omega + J^{-1}u \tag{8}$$

The six components of the moment of inertia are defined as

$$J = \begin{bmatrix} J_{11} & J_{12} & J_{13} \\ J_{12} & J_{22} & J_{23} \\ J_{13} & J_{23} & J_{33} \end{bmatrix} \tag{9}$$

In the form of vector notation, we define

$$p = [J_{11} \quad J_{22} \quad J_{33} \quad J_{12} \quad J_{13} \quad J_{23}]^T \tag{10}$$

### 2.3 Measurement model

The body angular velocity measurement equation at time  $t = t_k$  is expressed as

$$\tilde{\omega}_k = (I + M)\omega_k + b + v_{\omega k} \tag{11}$$

where  $\omega$  is the true body angular velocity,  $\tilde{\omega}$  is the angular velocity measurement vector,  $M$  is a matrix combined by the scale factor errors and the misalignments such as

$$M = \begin{bmatrix} \lambda_1 & \delta_{12} & \delta_{13} \\ \delta_{21} & \lambda_2 & \delta_{23} \\ \delta_{31} & \delta_{32} & \lambda_3 \end{bmatrix} \tag{12}$$

where  $b \in R^3$  is the bias error vector. The scale factor and the misalignment are written in vector form as

$$\lambda = [\lambda_1 \quad \lambda_2 \quad \lambda_3]^T \tag{13}$$

$$\delta = [\delta_{12} \quad \delta_{13} \quad \delta_{21} \quad \delta_{23} \quad \delta_{31} \quad \delta_{32}]^T$$

In this article, misalignment and bias error of the attitude sensor, usually given as a star tracker, are not assumed because those of the star trackers are usually less than those of the rate sensors.

### 3. Unscented Kalman filter

In this section, the unscented Kalman filter algorithm is presented. Ever since Julier and Uhlmann have proposed the algorithm, numerous modifications and enhancements have been reported. For estimation of parameters as well as state variables two methodologies are mainly employed – joint and dual filtering techniques. Between the two methods, the joint approach is easier and more intuitive to implement. Joint filters augment the original state variables with parameters to be estimated. Since parameters are usually assumed to be constant, time update of the filter model does not change the expanded parameter variables except its process noise if assumed. On the contrary, the dual method set up another filter for parameters so that two filters run sequentially in every step. The state estimator first propagates and updates for given measurements, and then the parameter estimator updates considering the updated output of the state variables as measurements. It is argued that the primary benefit of the dual UKF is being able to prevent erratic behaviour by decoupling the parameter filter from the state filter (VanDyke et al., 2004). However, the UKF in this problem converges only with the joint method as shown later. This section summarizes the UKF algorithm. This summary of the UKF equations follows the descriptions by Wan and van der Merwe (2000) and VanDyke et al. (2004).

#### 3.1 Joint estimation

The state variable and the parameter are noted by  $s \in \mathbb{R}^n$  and  $d \in \mathbb{R}^m$ , respectively. The augmented state variable of the joint filter is defined by

$$x = \begin{bmatrix} s^T & d^T \end{bmatrix}^T \quad (14)$$

The filter initialization is conducted with assumed mean and covariance of the augmented state vector.

$$\begin{aligned} \hat{x}(t_0) &= E\{\hat{x}_0\} \\ P_{x_0} &= E\left\{ (x(t_0) - \hat{x}_0)(x(t_0) - \hat{x}_0)^T \right\} \end{aligned} \quad (15)$$

Denoting  $L = n + m$ , the sigma points of  $L$  are generated using the *a priori* mean and covariance of the state as

$$\chi_{k-1} = \begin{bmatrix} \hat{x}_{k-1}^T & \hat{x}_{k-1}^T + \sqrt{(L + \gamma)P_{x_{k-1}}} & \hat{x}_{k-1}^T - \sqrt{(L + \gamma)P_{x_{k-1}}} \end{bmatrix}^T \quad (16)$$

where  $\gamma = \alpha^2(L + \kappa) - L$  is a scaling parameter.  $\alpha$  is usually set to a small positive value.  $\kappa$  is a secondary scaling parameter usually set to 0. The set of singular points,  $\chi_k$ , is  $L \times (2L + 1)$  matrix. Defining  $\chi_{i,k}$  as *i*th column of  $\chi_k$ , each sigma point is propagated through the nonlinear system

$$\chi_{i,k|k-1} = F(\chi_{i,k-1}, u_{k-1})^T \quad (17)$$

The posterior mean,  $\hat{x}_k^-$ , and the covariance,  $P_{xk}^-$ , are determined from the statistics of the propagated sigma points as follows:

$$\begin{aligned} \hat{x}_k^- &= \sum_{i=0}^{2L} W_i^m \chi_{i,k|k-1} \\ P_{xk}^- &= \sum_{i=0}^{2L} W_i^c (\chi_{i,k|k-1} - \hat{x}_k^-)(\chi_{i,k|k-1} - \hat{x}_k^-)^T + Q_{xk} \end{aligned} \tag{18}$$

$Q_{xk}$  is the process noise covariance of the system. The weights,  $W_i^m$  and  $W_i^c$ , are calculated by

$$\begin{aligned} W_0^m &= \frac{\gamma}{L + \gamma} \\ W_0^c &= \frac{\gamma}{L + \gamma} + 1 - \alpha^2 + \beta \\ W_i^c &= W_i^m = \frac{1}{2(L + \gamma)}, \quad i = 1, \dots, 2L \end{aligned} \tag{19}$$

$\beta$  is used to incorporate prior knowledge. For Gaussian distributions,  $\beta = 2$  is optimal. The estimated measurement vector  $\gamma_{i,k|k-1}$ ,  $i$ th column of matrix  $\Upsilon_{k|k-1} \in R^{l \times (2L+1)}$  is calculated by transforming the sigma points using the nonlinear measurement model,

$$\gamma_{i,k|k-1} = H(\chi_{i,k|k-1}) \tag{20}$$

The mean measurement,  $\hat{y}_k^-$ , and the measurement covariance,  $P_{ykyk}$ , are calculated based on the statistics of the transformed sigma points.

$$\begin{aligned} \hat{y}_k^- &= \sum_{i=0}^{2L} W_i^m \gamma_{i,k|k-1} \\ P_{ykyk} &= \sum_{i=0}^{2L} W_i^c (\gamma_{i,k|k-1} - \hat{y}_k^-)(\gamma_{i,k|k-1} - \hat{y}_k^-)^T + R_{yk} \end{aligned} \tag{21}$$

$R_{yk}$  is the measurement noise covariance matrix. The cross-correlation covariance,  $P_{xkyk}$ , is calculated using

$$P_{xkyk} = \sum_{i=0}^{2L} W_i^c (\chi_{i,k|k-1} - \hat{x}_k^-)(\gamma_{i,k|k-1} - \hat{y}_k^-)^T \tag{22}$$

The Kalman gain matrix is approximated from the cross-correlation and measurement covariances using

$$K_{xk} = P_{xkyk} P_{ykyk}^{-1} \tag{23}$$

The measurement update equations used to determine the mean,  $\hat{x}_k$ , and covariance,  $P_{xk}$ , of the filtered state are

$$\begin{aligned}\hat{x}_k &= \hat{x}_k^- + K_k (y_k - \hat{y}_k^-) \\ P_{xk} &= P_{xk}^- - K_k P_{ykyk} K_k^T\end{aligned}\quad (24)$$

### 3.2 Joint UKF state variables

In this paper, the state vector of the original system consists of the attitude quaternion and the angular rate. The attitude quaternion is a unique non-singular parameterization. However, quaternion has to satisfy unity constraint of the magnitude, which may result in covariance singularity if all the four elements are used. Therefore, only the vector components will be used in the UKF implementation.

Parameters to be estimated is six components of the moment of inertia, the scale factor error, six elements of misalignment, and the bias of the rate sensor as in Eqs. (10), (12), and (13). Therefore,

$$x = [\delta q_{13}^T \quad \omega^T \quad p^T \quad \lambda^T \quad \delta^T \quad b^T]^T \quad (25)$$

where

$$\delta q = \bar{q} \otimes \hat{q}^{-1} \quad (26)$$

Since the error quaternion is utilized, the state is initialized with

$$\hat{x}_{k-1} = [0_{3 \times 1}^T \quad \omega_{k-1}^T \quad p_{k-1}^T \quad \lambda_{k-1}^T \quad \delta_{k-1}^T \quad b_{k-1}^T]^T \quad (27)$$

Once the sigma points are calculated, quaternion component  $\delta q_{13,i}^z$  is used to obtain the four-element sigma point quaternion  $q_i^z$  to propagate the nonlinear model.

$$q_i^z = \left[ \delta q_{13,i}^z \quad \sqrt{1 - \delta q_{13,i}^z T \delta q_{13,i}^z} \right]^T \otimes \hat{q}_{k-1} \quad (28)$$

The parameters are assumed to be constant.

$$\begin{aligned}\dot{p} &= 0 \\ \dot{\lambda} &= 0 \\ \dot{\delta} &= 0 \\ \dot{b} &= 0\end{aligned}\quad (29)$$

Now, Eqs. (6), (8) and (29) constitute the nonlinear system model of the UKF. And, lastly the following is the measurement equation.

$$\begin{aligned}\delta \tilde{q}_{13,k} &= \delta q_{13,k} + v_{qk} \\ \tilde{\omega}_k &= (I + M)\omega_k + b + v_{\omega k}\end{aligned}\quad (30)$$

After model propagation, three component of error quaternion is calculated again. After measurement update of Eq. (24), four-element quaternion can be determined using

$$\hat{q}_k = \left[ \delta \hat{q}_{13,k}^T \quad \sqrt{1 - \delta \hat{q}_{13,k}^T \delta \hat{q}_{13,k}} \right]^T \otimes \hat{q}_{k-1} \quad (31)$$

More detailed and helpful discussion on quaternion-based computation can refer (Kraft, 2003).

#### 4. Numerical simulation results

In this section, simulation results for hybrid estimation of states, the moment of inertia and the rate sensor calibration will be presented. The joint UKF will be compared to the results using EKF (Myung et al., 2007).

##### 4.1 Simulation conditions

In order to estimate the inertia matrix and the gyro calibration parameters, ‘persistent excitation’ of motion should be guaranteed. A constant body angular velocity vector or one with constant direction will not satisfy this requirement.

As one of the reference trajectories satisfying the ‘persistent excitation’ condition (Pittelkau, 2001), the following rate trajectory is proposed (Myung et al., 2007).

$$\omega_r = \phi \dot{l} - (1 - \cos \phi) \dot{l} \times \dot{l} + \dot{l} \sin \phi$$

where

$$\begin{aligned} \phi &= 50\pi t (\text{rad}) \\ I &= \begin{bmatrix} \sin \omega_1 t \sin \omega_2 t \\ \cos \omega_1 t \sin \omega_2 t \\ \cos \omega_2 t \end{bmatrix} \\ \omega_1 &= 0.01 \text{ rad/s} \\ \omega_2 &= 0.004 \text{ rad/s} \end{aligned}$$

For simulation purposes, a predictive controller (Crassidis et al., 1997) is applied to the spacecraft attitude control. Given reference trajectories to follow, the predictive control synthesizes control command based on nonlinear state prediction strategy using the Taylor series expansion. The reference trajectories are shown in Fig. 1 and Fig. 2.

##### 4.2 Simulation results

The following true system and alignment parameters are assumed (Myung et al., 2007):

$$\begin{aligned} J &= \begin{bmatrix} 200 & 50 & -30 \\ 50 & 240 & 10 \\ -30 & 10 & 100 \end{bmatrix} \text{ kgm} / \text{s}^2 \\ \lambda &= [5000, -1000, -2000]^T \text{ ppm} \\ \delta &= [648, 1296, 972, 648, -648, 1296]^T \text{ arcs} \\ b &= [5, 3, 2]^T \times 10^{-4} \text{ rad} / \text{s} \end{aligned}$$

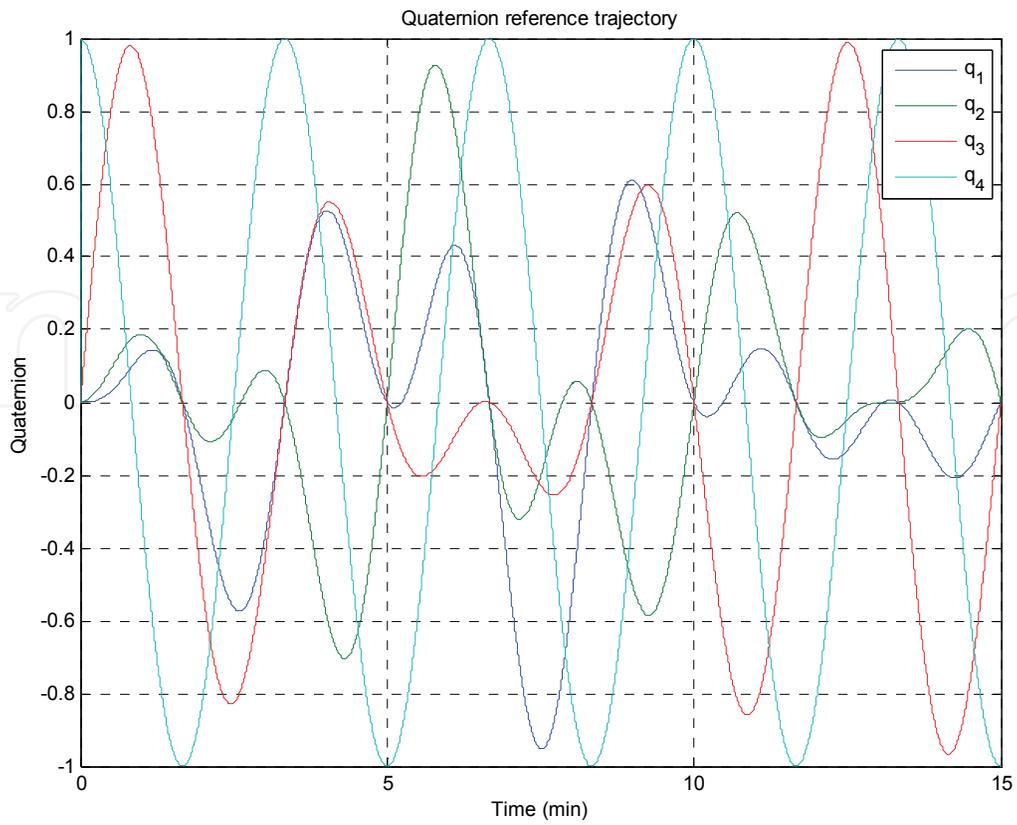


Fig. 1. Quaternion reference trajectory

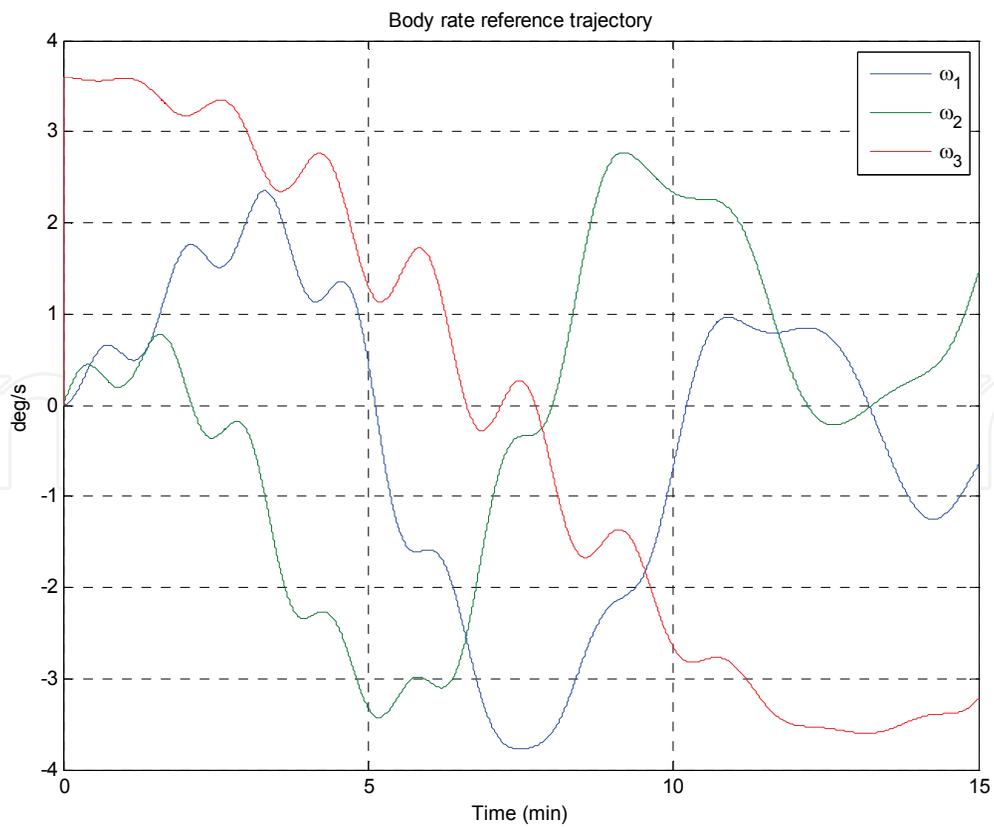


Fig. 2. Body angular rate reference trajectory

Nominal values of the parameters are given as

$$J = \begin{bmatrix} 160 & 20 & -20 \\ 20 & 160 & -20 \\ -20 & -20 & 160 \end{bmatrix} \text{ kgm} / \text{s}^2$$

$$\lambda = [0 \ 0 \ 0]^T \text{ ppm}$$

$$\delta = [0 \ 0 \ 0 \ 0 \ 0 \ 0]^T \text{ arcs}$$

$$b = [0 \ 0 \ 0]^T \text{ rad} / \text{s}$$

The process and the measurement noise covariance matrices are designated as

$$Q = 10^{-8} I_{3 \times 3} \text{ rad}^2 / \text{s}^4$$

$$R_q = 10^{-6} I_{3 \times 3} \text{ rad}^2$$

$$R_\omega = 10^{-5} I_{3 \times 3} \text{ rad}^2 / \text{s}^2$$

Simulation is performed for 15 min. The star tracker and the rate sensor measurements are assumed to be given every 0.2 s. Table 1 - 4 present estimation error comparison of the EKF and UKF by Monte-Carlo simulation of 20 runs. The upper data in each cell of the tables are percentage error with respect to own value. The lower data are normalized values of the final covariances. Therefore, smaller values are more accurate regardless of magnitude of the nominal parameter values. The moment of inertia estimation is very accurate for both EKF and UKF in Table 1. However, rate sensor calibration results of the UKF are much more accurate than those of EKF. If the reference trajectory is designed considering excitation optimality, estimation results will be even more accurate (Sekhavat, 2009).

	units	J <sub>11</sub> (1σ)	J <sub>22</sub> (1σ)	J <sub>33</sub> (1σ)	J <sub>12</sub> (1σ)	J <sub>13</sub> (1σ)	J <sub>23</sub> (1σ)
EKF	% error	0.140	0.163	0.527	0.137	0.319	0.548
	%	(0.106)	(0.096)	(0.250)	(0.279)	(0.310)	(0.847)
UKF	% error	0.080	0.073	0.185	0.072	0.023	0.063
	%	(0.879)	(0.788)	(1.793)	(0.832)	(1.577)	(4.495)

Table 1. Moment of inertia estimation results of EKF and UKF by Monte-Carlo Simulation

	units	λ <sub>1</sub> (1σ)	λ <sub>2</sub> (1σ)	λ <sub>3</sub> (1σ)
EKF	% error	53.9	56.3	13.7
	%	(82.4)	(205.6)	(117.0)
UKF	% error	1.17	61.8	18.8
	%	(32.0)	(138.0)	(55.3)

Table 2. Rate sensor scale factor error estimation results of EKF and UKF by Monte-Carlo Simulation

	units	$\delta_{12}$ ( $1\sigma$ )	$\delta_{13}$ ( $1\sigma$ )	$\delta_{21}$ ( $1\sigma$ )	$\delta_{23}$ ( $1\sigma$ )	$\delta_{31}$ ( $1\sigma$ )	$\delta_{32}$ ( $1\sigma$ )
EKF	% error	91.2	121.9	72.0	103.8	59.6	14.0
	%	(87.1)	(47.6)	(75.0)	(72.9)	(85.0)	(64.1)
UKF	% error	28.3	6.81	13.5	7.74	6.51	10.9
	%	(49.3)	(18.3)	(32.9)	(34.3)	(46.2)	(26.9)

Table 3. Rate sensor misalignment estimation results of EKF and UKF by Monte-Carlo Simulation

	units	$b_1$ ( $1\sigma$ )	$b_2$ ( $1\sigma$ )	$b_3$ ( $1\sigma$ )
EKF	% error	267.1	166.1	37.7
	%	(29.6)	(47.6)	(67.9)
UKF	% error	2.46	11.6	1.93
	%	(9.63)	(16.0)	(23.8)

Table 4. Rate sensor bias estimation results of EKF and UKF by Monte-Carlo Simulation

Fig. 3 to Fig. 10 illustrates one of the UKF simulation results with time. Each variable has different convergence time constant. The attitude and the rate converge very fast as in Fig. 3 and Fig. 4. And then the moment of inertia components converge. And finally calibration parameters converge.

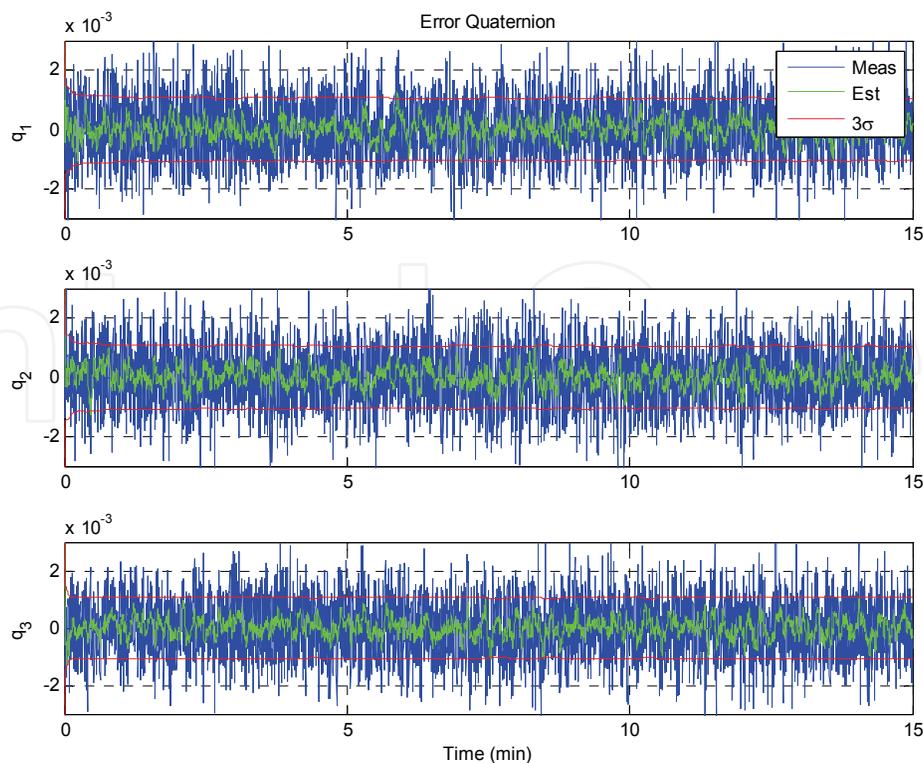


Fig. 3. Attitude estimation error with  $3\sigma$  bounds

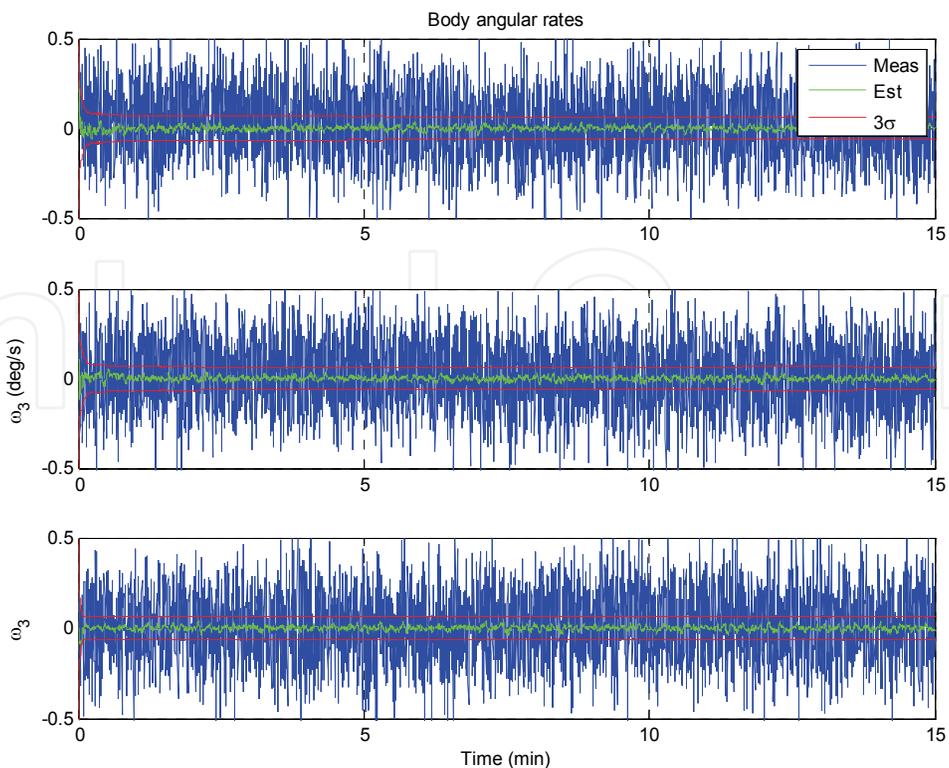


Fig. 4. Angular velocity estimation error with  $3\sigma$  bounds

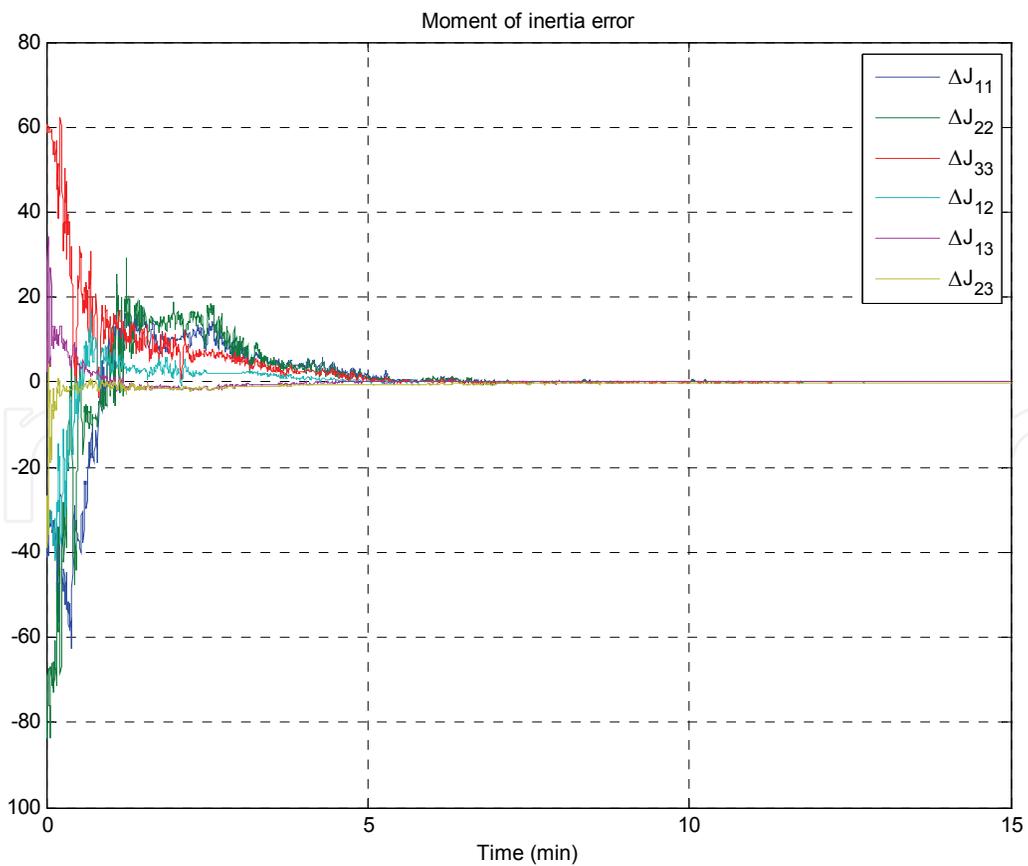


Fig. 5. Moment of inertia estimation error

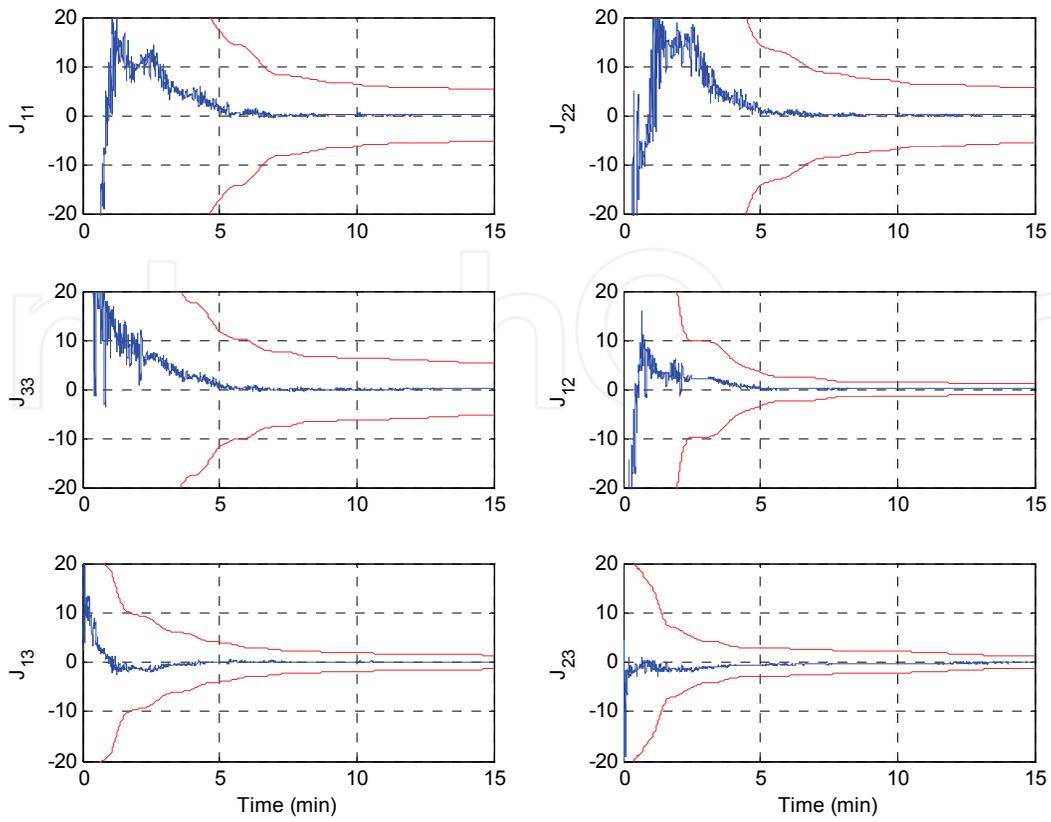


Fig. 6. Moment of inertia estimation error with  $3\sigma$  bounds

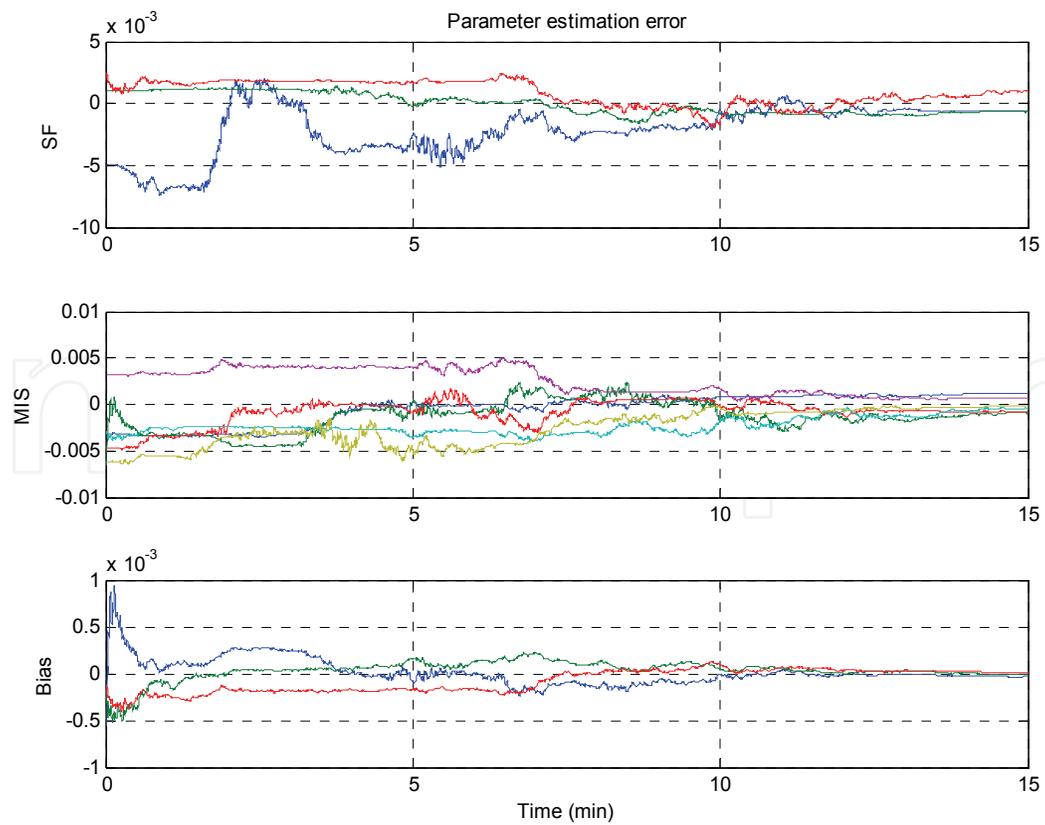


Fig. 7. Rate sensor calibration error

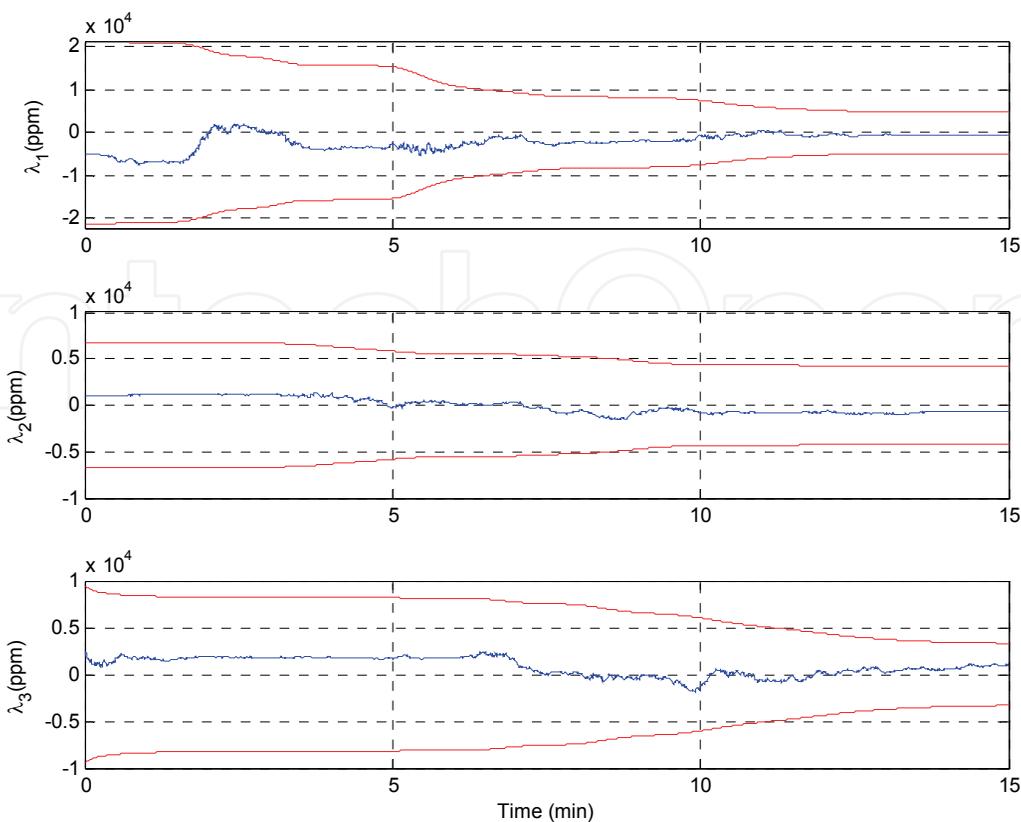


Fig. 8. Rate gyro scale factor estimation error with  $3\sigma$  bounds

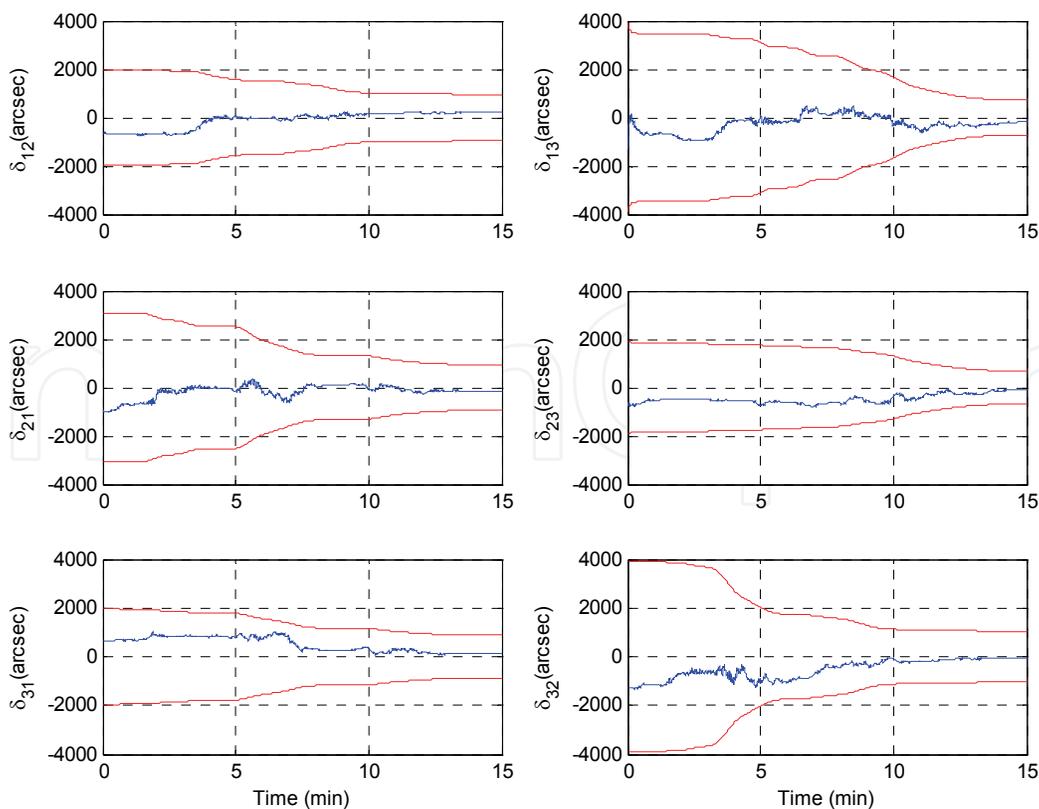


Fig. 9. Rate gyro misalignment estimation error with  $3\sigma$  bounds

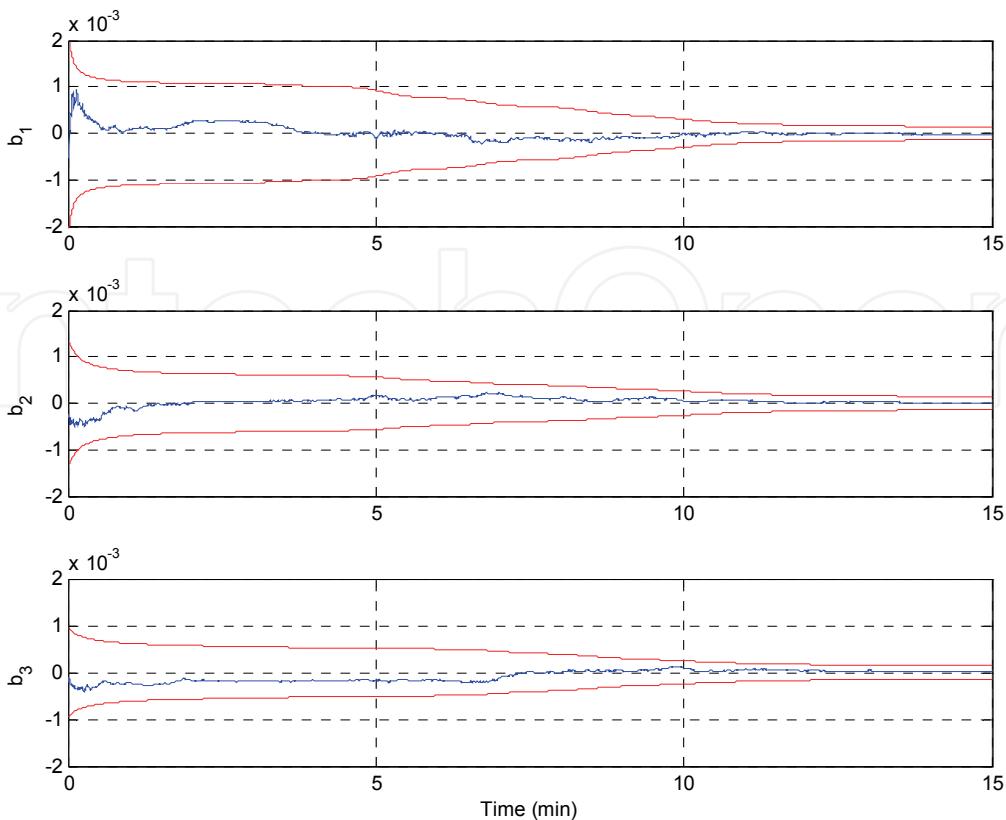


Fig. 10. Rate gyro bias estimation error with  $3\sigma$  bounds

## 5. Conclusions

This study presented hybrid estimation of the moment of inertia of spacecraft and calibration parameters of the rate sensor such as the scale factor error, six elements of misalignment and the gyro bias error during a single estimation maneuver. For this purpose, a joint unscented Kalman filter (UKF) algorithm was successfully applied and the performance was compared to the results using the extended Kalman filter (EKF). While the components of the moment of inertia were estimated very accurately by both the EKF and the UKF, the rate sensor calibration parameters – scale factor, misalignment, and bias error – were filtered much better by the UKF than the EKF. Simulation results demonstrated applicability and performance for spacecraft system identification and the gyro calibration simultaneously.

This concept of estimation procedure can reduce efforts and costs for periodic parameter estimation and gyro calibration of spacecraft in-orbit. Also, proposed method can be extended to calibration maneuvers of other equipments such as star trackers and optical payloads.

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The development and launch of the first artificial satellite Sputnik more than five decades ago propelled both the scientific and engineering communities to new heights as they worked together to develop novel solutions to the challenges of spacecraft system design. This symbiotic relationship has brought significant technological advances that have enabled the design of systems that can withstand the rigors of space while providing valuable space-based services. With its 26 chapters divided into three sections, this book brings together critical contributions from renowned international researchers to provide an outstanding survey of recent advances in spacecraft technologies. The first section includes nine chapters that focus on innovative hardware technologies while the next section is comprised of seven chapters that center on cutting-edge state estimation techniques. The final section contains eleven chapters that present a series of novel control methods for spacecraft orbit and attitude control.

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