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# A novel two-stage extended Kalman filter algorithm for reaction flywheels fault estimation



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Two-stage extended Kalman filter

**Abstract** This paper investigates the problem of two-stage extended Kalman filter (TSEKF)-based fault estimation for reaction flywheels in satellite attitude control systems (ACSs). Firstly, based on the separate-bias principle, a satellite ACSs with actuator fault is transformed into an augmented nonlinear discrete stochastic model; then, a novel TSEKF is suggested such that it can simultaneously estimate satellite attitude information and actuator faults no matter they are additive or multiplicative; finally, the proposed approach is respectively applied to estimating bias faults and loss of effectiveness for reaction flywheels in satellite ACSs, and simulation results demonstrate the effectiveness of the proposed fault estimation approach.

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## 1. Introduction

The separate-bias estimation algorithm is used to estimate the state and constant bias of linear systems. The basic principle of this algorithm, which is also called two-stage Kalman filter (TSKF), is to estimate system states and constant biases separately, then obtain the optimal estimate using the coupling relationship between them. In 1969, Friedland firstly proposed the separate-bias estimation algorithm<sup>1</sup> and made a further investigation.<sup>2,3</sup> During the past four decades, many research achievements have been reported on this algorithm. At

present, the main research on this topic is concerned with estimation of constant/time-varying bias and all kinds of engineering applications.

Recently, many scholars have paid considerable attention to separate-bias estimation algorithm for linear systems.<sup>4–6</sup> Keller and Darouach<sup>4</sup> suggested an optimal solution of the TSKF, which can be used to estimate optimal state and optimal random bias, and further a two-stage optimal strategy was developed for discrete-time stochastic linear systems subject to intermittent unknown inputs.<sup>5</sup> Khabbazi and Esfanjani<sup>6</sup> proposed a constrained TSKF for tracking control problem in an uncertain linear system and its main advantage is the improvement of estimation accuracy.

For fault/bias estimation of nonlinear systems, much progress has been made on EKF-based approaches. EKF-based sub-optimal algorithm was proposed in Ref.<sup>7</sup>. Zhou et al. investigated a pseudo separate-bias estimation algorithm for nonlinear time-varying stochastic systems.<sup>8,9</sup> In Ref.<sup>10</sup>, fuzzy

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Kalman filter-based approach was proposed for nonlinear stochastic discrete time systems.

Based on the general TSKF, Hsieh<sup>11</sup> proposed a general two-stage extended Kalman filter (GTSEKF)-based constant parameter estimation approach. In Ref.<sup>12</sup>, an adaptive TSEKF like Ref.<sup>11</sup> was proposed to estimate the closed-loop position and speed of sensorless control for permanent magnet synchronous motor. Kim<sup>13</sup> proposed an adaptive TSEKF for INS-GPS loosely coupled systems and its main advantage was it cost less computation time due to the introduction of the forgetting factor. In Ref.<sup>14</sup>, an adaptive TSEKF algorithm based on Ref.<sup>13</sup> was introduced to the application of geomagnetic aided inertial navigation filtering. By introducing strong tracking multiple fading factors and embedding EKF into an optimal TSKF, a novel robust filter-based bearings-only maneuvering target tracking problem was investigated, which can provide an optimal estimation of the target state and the unknown statistical parameters of virtual noises.<sup>15</sup>

The faults of actuators and sensors in control systems can be represented as biases via separate-bias estimation algorithm. Fault estimation for dynamic systems has attracted considerable attention during the past two decades. When estimating the additive actuator/sensor faults, the algorithm can be implemented easily since the biases representing faults in these models have specific physical meanings and the principles are clear.<sup>16</sup> When estimating the multiplicative faults in actuators, it is necessary to use other parameters to represent the fault models, such as control effectiveness factors, which can be used to indicate the fault degree of control systems. By introducing forgetting factors into the optimal TSKF in Ref.<sup>4</sup>, an adaptive TSKF was exploited to estimate the abrupt reduction of control effectiveness in dynamic systems by Wu et al.<sup>17</sup> This algorithm is applied for the identification of impairment in its control surfaces in an aircraft model. In Refs.<sup>18–22</sup>, a further investigation on this algorithm was made and widely applied it on fault diagnosis and fault-tolerant control. In Ref.<sup>23</sup>, control effectiveness factor estimation was extended to the estimation of control distribution matrix elements, and the TSKF was applied to actuator/surface fault diagnosis and fault-tolerant control of F-16. In recent years, this method has been applied to the fault diagnosis and fault-tolerant control of sensors and actuators in satellite attitude control system.<sup>16,24–26</sup> The value of the effectiveness factors can be derived via this method and system fault degree can be analyzed to obtain biases for the fault-tolerant control purpose. In addition, to the best of our knowledge, separate-bias principle never considers additive faults and multiplicative faults simultaneously.

In view of this, this paper investigates TSEKF-based fault estimation for reaction flywheels in satellites. A novel TSEKF is suggested such that it can simultaneously estimate satellite attitude information and reaction flywheel faults no matter they are additive or multiplicative. It is respectively applied to estimating bias faults and loss of effectiveness for reaction flywheels in a satellite ACSs, and the simulation results demonstrate the effectiveness of the proposed fault estimation approach.

## 2. System fault model

Consider the following nonlinear discrete-time stochastic system with bias vector of unknown magnitude  $\mathbf{b}_k \in \mathbf{R}^p$ :

$$\begin{cases} \mathbf{x}_{k+1} = \mathbf{f}_k(\mathbf{x}_k, \mathbf{b}_k) + \mathbf{w}_k^x, & \mathbf{b}_{k+1} = \mathbf{b}_k + \mathbf{w}_k^b \\ \mathbf{y}_k = \mathbf{h}_k(\mathbf{x}_k, \mathbf{b}_k) + \mathbf{v}_k \end{cases} \quad (1)$$

where  $\mathbf{x}_k \in \mathbf{R}^n$  is the system state;  $\mathbf{y}_k \in \mathbf{R}^m$  is the measurement vector; the noise sequence  $\mathbf{w}_k^b$ ,  $\mathbf{w}_k^x$  and  $\mathbf{v}_k$  are zero-mean uncorrelated Gaussian random sequences with

$$E \left( \begin{bmatrix} \mathbf{w}_k^b \\ \mathbf{w}_k^x \\ \mathbf{v}_k \end{bmatrix} \begin{bmatrix} \mathbf{w}_j^{bT} & \mathbf{w}_j^{xT} & \mathbf{v}_j^T \end{bmatrix} \right) = \begin{bmatrix} \mathbf{W}^b & & \\ & \mathbf{W}^x & \\ & & \mathbf{V} \end{bmatrix} \delta_{k,j} \quad (2)$$

where  $\mathbf{W}^b > \mathbf{0}$ ,  $\mathbf{W}^x > \mathbf{0}$ ,  $\mathbf{V} > \mathbf{0}$  and  $\delta_{k,j}$  is the Kronecker delta. The initial states  $\mathbf{x}_0$  and  $\mathbf{b}_0$  are Gaussian random variables with  $\hat{\mathbf{x}}_0 = E(\mathbf{x}_0)$ ,  $\hat{\mathbf{b}}_0 = E(\mathbf{b}_0)$ ,  $\bar{\mathbf{P}}_0^x = E(\mathbf{x}_0 - \hat{\mathbf{x}}_0)(\mathbf{x}_0 - \hat{\mathbf{x}}_0)^T$ ,  $\bar{\mathbf{P}}_0^b = E(\mathbf{b}_0 - \hat{\mathbf{b}}_0)(\mathbf{b}_0 - \hat{\mathbf{b}}_0)^T$  and  $\bar{\mathbf{P}}_0^{xb} = E(\mathbf{x}_0 - \hat{\mathbf{x}}_0)(\mathbf{b}_0 - \hat{\mathbf{b}}_0)^T$ . The function  $\mathbf{f}_k(\mathbf{x}_k, \mathbf{b}_k)$  and  $\mathbf{h}_k(\mathbf{x}_k, \mathbf{b}_k)$  are assumed to be continuous and can be expanded by Taylor series expansion. If the higher order terms can be neglected, the linear discrete-time stochastic system Eq. (1) appears in the following form:

$$\begin{cases} \mathbf{x}_{k+1} = \mathbf{A}_k \mathbf{x}_k + \mathbf{F}_k^a \mathbf{b}_k + \mathbf{w}_k^x + \mathbf{M}_k, & \mathbf{b}_{k+1} = \mathbf{b}_k + \mathbf{w}_k^b \\ \mathbf{y}_k = \mathbf{C}_k \mathbf{x}_k + \mathbf{F}_k^s \mathbf{b}_k + \mathbf{v}_k + \mathbf{N}_k \end{cases} \quad (3)$$

where  $\mathbf{A}_k \in \mathbf{R}^{n \times n}$  and  $\mathbf{C}_k \in \mathbf{R}^{m \times n}$  are state transition matrix and observation matrix, respectively, and we have

$$\begin{cases} \mathbf{A}_k = \frac{\partial \mathbf{f}}{\partial \mathbf{x}^T} \Big|_{\mathbf{x} = \mathbf{x}_{k|k}, \mathbf{b} = \mathbf{b}_{k|k}}, & \mathbf{F}_k^a = \frac{\partial \mathbf{f}}{\partial \mathbf{b}^T} \Big|_{\mathbf{x} = \mathbf{x}_{k|k}, \mathbf{b} = \mathbf{b}_{k|k}} \\ \mathbf{C}_k = \frac{\partial \mathbf{h}}{\partial \mathbf{x}^T} \Big|_{\mathbf{x} = \mathbf{x}_{k|k-1}, \mathbf{b} = \mathbf{b}_{k|k-1}}, & \mathbf{F}_k^s = \frac{\partial \mathbf{h}}{\partial \mathbf{b}^T} \Big|_{\mathbf{x} = \mathbf{x}_{k|k-1}, \mathbf{b} = \mathbf{b}_{k|k-1}} \\ \mathbf{M}_k = \mathbf{f}_k(\mathbf{x}_{k|k}, \mathbf{b}_{k|k}) - \mathbf{A}_k(\mathbf{x}_{k|k}, \mathbf{b}_{k|k})\mathbf{x}_{k|k} - \mathbf{F}_k^a(\mathbf{x}_{k|k}, \mathbf{b}_{k|k})\mathbf{b}_{k|k} \\ \mathbf{N}_k = \mathbf{h}_k(\mathbf{x}_{k|k-1}, \mathbf{b}_{k|k-1}) - \mathbf{C}_k(\mathbf{x}_{k|k-1}, \mathbf{b}_{k|k-1})\mathbf{x}_{k|k-1} \\ \quad - \mathbf{F}_k^s(\mathbf{x}_{k|k-1}, \mathbf{b}_{k|k-1})\mathbf{b}_{k|k-1} \end{cases} \quad (4)$$

where  $\mathbf{x}_{k|k}$  and  $\mathbf{b}_{k|k}$  denote the optimal results of  $\mathbf{x}_k$  and  $\mathbf{b}_k$  respectively.

The vector function  $\boldsymbol{\omega} = [\omega_x, \omega_y, \omega_z]^T$  represents the inertially referenced satellite angular rate vector of the satellite body relative to the inertial coordinate system and the corresponding Euler angles are  $\varphi$ ,  $\theta$  and  $\psi$ . Define  $\mathbf{x} = [\omega_x, \omega_y, \omega_z, \varphi, \theta, \psi]^T$ , the state equation of satellite attitude control system based on the satellite attitude dynamics equation can be given as

$$\dot{\mathbf{x}} = \mathbf{g}(\mathbf{x}) + \mathbf{B}\mathbf{u}(\mathbf{x}) \quad (6)$$

where

$$\begin{cases} \mathbf{g}(\mathbf{x}) = \begin{bmatrix} \mathbf{I}_s^{-1}(-\boldsymbol{\omega} \times \mathbf{I}_s \boldsymbol{\omega}) \\ \boldsymbol{\Phi}(\mathbf{x}) \end{bmatrix} \\ \boldsymbol{\Phi}(\mathbf{x}) = \frac{1}{\cos \varphi} \begin{bmatrix} \cos \varphi \cos \theta & 0 & \cos \varphi \sin \theta \\ \sin \varphi \sin \theta & \cos \varphi & -\sin \varphi \cos \theta \\ -\sin \theta & 0 & \cos \theta \end{bmatrix} \boldsymbol{\omega} \\ \mathbf{B} = \begin{bmatrix} \mathbf{I}_s^{-1} \\ \mathbf{0} \end{bmatrix} \end{cases} \quad (7)$$

$\mathbf{u}(\mathbf{x}) \in \mathbf{R}^l$  is the known control input vector;  $\mathbf{B} \in \mathbf{R}^{n \times l}$  is the control input matrix;  $\mathbf{I}_s$  is the moment of inertial matrix of the satellite.

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