Acta Astronautica 134 (2017) 159–169

Contents lists available at ScienceDirect

Acta Astronautica

journal homepage: www.elsevier.com/locate/actaastro

# Fault estimation of satellite reaction wheels using covariance based adaptive unscented Kalman filter

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ARTICLE INFO

*Keywords:*
Satellite attitude control actuator
Reaction wheel
Fault estimation
Parameter tracking
Adaptive unscented Kalman filter

ABSTRACT

Reaction wheels, as one of the most commonly used actuators in satellite attitude control systems, are prone to malfunction which could lead to catastrophic failures. Such malfunctions can be detected and addressed in time if proper analytical redundancy algorithms such as parameter estimation and control reconfiguration are employed. Major challenges in parameter estimation include speed and accuracy of the employed algorithm. This paper presents a new approach for improving parameter estimation with adaptive unscented Kalman filter. The enhancement in tracking speed of unscented Kalman filter is achieved by systematically adapting the covariance matrix to the faulty estimates using innovation and residual sequences combined with an adaptive fault annunciation scheme. The proposed approach provides the filter with the advantage of tracking sudden changes in the system non-measurable parameters accurately. Results showed successful detection of reaction wheel malfunctions without requiring *a priori* knowledge about system performance in the presence of abrupt, transient, intermittent, and incipient faults. Furthermore, the proposed approach resulted in superior filter performance with less mean squared errors for residuals compared to generic and adaptive unscented Kalman filters, and thus, it can be a promising method for the development of fail-safe satellites.

## 1. Introduction

Reaction wheels are the most commonly used actuators in spacecraft attitude control system; they are prone to malfunction which could lead to catastrophic failures. Such malfunctions can be detected and addressed in time if proper analytical redundancy algorithms such as parameter estimation and control reconfiguration are employed. Major challenges in parameter estimation include speed and accuracy of the employed algorithm. The problem of accurately and promptly tracking changes in system parameters for mechanical systems has been of constant interest for the purpose of system monitoring and control [1–4]. Analytical redundancy, as one of the major subsidies in this field, has evolved to remedy the shortcomings of hardware redundancy for complex systems. Such shortcomings include major budged constraints, space limitations for design and manufacturing, concerns with safety and reliability, etc. One of the major challenges in system monitoring and fault detection is to achieve the ability for tracking sudden changes in non-measurable system parameters; this becomes more challenging when the system under study is nonlinear and complex. Reaction wheels (RW), as one of the most commonly used actuators in spacecraft attitude control system, can be considered as such and are prone to hardware failures [5]. Sudden changes in non-measurable RW parameters can occur while operating in space. If such changes are not tracked precisely and with reasonable delay, catastrophic failures could occur. Therefore, an algorithm that could estimate parameters and track sudden changes accurately can help developing fail-safe satellites where hardware redundancy is not possible due to limited space and power.

Several researchers have examined the problem of fault detection, isolation, and identification [1–4]. Gertler [1] has surveyed all model-based methods for fault detection and concludes that major quality issues for failure detection algorithms are isolability, sensitivity, and robustness. Marzat et al. [2] have reviewed model-based fault diagnosis approaches for aerospace systems; these approaches include expert systems [6], neural networks [7–9], support vector machine (SVM) [10–12], principal component analysis (PCA) [13–16], parameter estimation [17,18], Kalman filters (KF) [19–21], unscented Kalman filters (UKF) [22–26]. More recently, Gao et al. [3,4] have comprehensively reviewed fault diagnosis approaches and their applications from model and signal-based perspectives. The reviewed literature suggests advantages of using Kalman filters as: small false alarm rate, short detection delay, robustness to model uncertainty, and isolation of simultaneous faults with the only shortcoming being restrictive Gaussian noise assumption. In addition, parameter estimation using Kalman filters is considered as an effective approach for structural

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http://dx.doi.org/10.1016/j.actaastro.2017.02.003
Received 13 January 2017; Accepted 3 February 2017
Available online 07 February 2017

damage detection with the shortcoming of non-applicability for on-line identification due to time delays. When sudden changes are expected, off-line tuning of the estimators is not acceptable. Therefore, an approach that can track non-measurable system parameters is required. In the previous study, the authors of this paper have proposed a parameter tracking approach based on adaptive unscented Kalman filters [24]. The suggested approach suffers from some limitations to be addressed in the present paper as follows: (1) The system model used in [24], neglects some of the stochastic components that could in fact adversely affects simulation results. In the current study, missing components are considered in the system model. (2) The adaption system in [24] considers only system and measurement noise covariances and the optimization process is done off-line. This approach suffers from lack of agility when abrupt faults occur, even after algorithm parameters are optimized. In addition, this approach was not examined for incipient faults. In the present investigation, states error covariance matrix is also considered when abrupt changes occur to ensure agile tracking of non-measurable system parameters. (3) The fault scenario in [24] only includes abrupt fault while in practical situations, transient, intermittent, and incipient faults also occur. In the current study, all mentioned fault cases are considered.

The contents of this paper are organized as follows: the standard UKF formulation is presented in Section 2 while Section 3 explains the proposed enhancement scheme for covariance adaptation. In Section 4, the mathematical model of the reaction wheel system is described while Section 5 presents results and discussions on four major fault scenarios at two noise levels. Finally, the conclusions of the present investigation are presented in Section 6.

## 2. Standard UKF

In order to explain the proposed approach, the parameter estimation with the assumption that the full state measurement is available is first presented based on the standard UKF.

Consider the following nonlinear discrete stochastic system

$$\begin{cases} X_k = f(X_{k-1}) + w_k \\ Z_k = g(X_k) + v_k \end{cases} \tag{1}$$

where $X_k \in \mathbb{R}^n$ is the state vector at time step $k$, $Z_k \in \mathbb{R}^m$ is the measurement vector,$w_k \in \mathbb{R}^n$ is the additive process noise, $v_k \in \mathbb{R}^m$ is the additive measurement noise, $f(\bullet)$ is a nonlinear process model, and $g(\bullet)$ is nonlinear measurement model. The process and measurement noises are assumed to be uncorrelated zero-mean Gaussian white noises with covariances $E[w_k w_j^T] = Q_k \delta_{kj}$, $E[v_k v_j^T] = R_k \delta_{kj}$, respectively. The process noise covariance $Q_k$ is non-negative definite, the measurement noise covariance $R_k$ is positive definite, and $\delta_{kj}$ is the Kronecker-$\delta$ function. When the system equation is in continuous form as

$$\dot{x} = f(x, u, t) + w \tag{2}$$

It can be transformed to the discrete domain using

$$X_k = X_{k-1} + \int_{(k-1)\Delta t}^{k\Delta t} f(x, u, t)dt \tag{3}$$

where $\Delta t$ or $T_s$ is discretization step size or sampling time. The integration can be carried out using the fourth order Runge-Kutta(RK4) method. The formulation for parameter estimation of a nonlinear discrete stochastic system using UKF [27] with minor modifications [28] can be described in the following steps:

1) ***Compute weights***

$$\mathbf{W}_0^{(m)} = \frac{\kappa}{n+\kappa}; \mathbf{W}_0^{(c)} = \frac{\kappa}{n+\kappa} + (1-\alpha^2+\lambda); \mathbf{W}_i^{(m)} = \mathbf{W}_i^{(c)} = \frac{1}{2(n+\kappa)} \tag{4}$$

2) ***Establish symmetric sigma points about the state estimate***

$$\hat{\boldsymbol{\chi}}_0 = \hat{\mathbf{x}}_{p(k+1)}^- \tag{5}$$

$$\hat{\boldsymbol{\chi}}_i = \hat{\mathbf{x}}_{p(k+1)}^- \pm \sqrt{(n+\kappa)\mathbf{P}_{\mathbf{xx}(k+1)i}^-}, \quad \forall i=1, 2, \ldots, n \tag{6}$$

3) ***Predict mean and covariance of states***

$$\mathbf{P}_{\mathbf{xx}k+1}^- = \mathbf{P}_{\mathbf{xx}k}^- + \mathbf{Q}_{k+1} \tag{7}$$

$$\mathbf{x}_{p(k+1)}^- = \mathbf{x}_{pk}^+ \tag{8}$$

4) ***Instantiate sigma points through measurement model***

$$\mathbf{Y}_i = g(\hat{\boldsymbol{\chi}}_i) \tag{9}$$

5) ***Predict mean and covariance of measurements***

$$\bar{\mathbf{y}} = \sum_{i=0}^{2n} W_i \mathbf{Y}_i \tag{10}$$

$$\mathbf{P}_{yy} = \sum_{i=0}^{2n} W_i [\mathbf{Y}_i - \bar{\mathbf{y}}][\mathbf{Y}_i - \bar{\mathbf{y}}]^T + \mathbf{R}_{k+1} \tag{11}$$

6) ***Predict cross covariance***

$$\mathbf{P}_{xy} = \sum_{i=0}^{2n} W_i [\hat{\boldsymbol{\chi}}_i - \hat{\mathbf{x}}_{p(k+1)}^-][\mathbf{Y}_i - \bar{\mathbf{y}}]^T \tag{12}$$

7) ***Calculate gain and update***

$$\mathbf{K}_{k+1} = \mathbf{P}_{xy}\mathbf{P}_{yy}^{-1} \tag{13}$$

$$\hat{\mathbf{x}}_{p(k+1)}^+ = \mathbf{x}_{p(k+1)}^- + \mathbf{K}_{k+1}(\mathbf{y} - \bar{\mathbf{y}}) \tag{14}$$

$$\mathbf{P}_{\mathbf{xx}k+1}^+ = \mathbf{P}_{\mathbf{xx}k+1}^- - \mathbf{K}_{k+1}\mathbf{P}_{yy}\mathbf{K}_{k+1}^T \tag{15}$$

where the $\sqrt{(n+\kappa)\mathbf{P}_{\mathbf{xx}_i}^-}$ terms denote the scaled $i^{th}$ rows or columns of $\sqrt{\mathbf{P}_{\mathbf{xx}}^-}$, $\boldsymbol{W}^{(m)}$ is the component weight for mean calculation, $\boldsymbol{W}^{(c)}$ is the component weight for covariance calculation, $n$ is the dimension of the states, $\kappa \geq 0$, $0 \leq \alpha < 1$, and $\lambda \geq 0$ are the control factors for the spread of sigma points, $\bar{\boldsymbol{y}}$ is the mean of variable $y$, $\boldsymbol{P}_{yy}$ is the covariance of measurements matrix, $\boldsymbol{x}$ is the n-state random variable, $\hat{x}$ is the initial sigma point, $\boldsymbol{P}_{xx}$ is the posteriori estimates covariance matrix, $\boldsymbol{Y}_i$ is the result of instantiated sigma points through measurement model, $\boldsymbol{P}_{xy}$ is the cross covariance matrix, $\boldsymbol{K}$ is the Kalman filter gain, and + and - superscripts show the pre-process and post-process values at each iteration, respectively.

## 3. Adaptive scheme

The adaptive scheme consists of three major parts: (1) adapting process and measurement noises, (2) detecting fault occurrence, (3) adapting states/parameters covariance matrix.

### *3.1. Process and measurement covariance*

The following adaptive mechanism is used to adjust process and measurement noise covariance matrices on-line [29]. The approach is adapted from [24] where the algorithm parameters are optimized off-line for specific abrupt fault scenarios. First Eq. (7) is re-written as