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A robust strong tracking cubature Kalman filter for spacecraft attitude estimation with quaternion constraint

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ABSTRACT

This paper considers a robust strong tracking nonlinear filtering problem in the case there are model uncertainties including the model mismatch, unknown disturbance and status mutation in the spacecraft attitude estimation system with quaternion constraint. Two multiple fading factor matrices are employed to regulate the prediction error covariance matrix, which guarantees its symmetry. The spherical-radial cubature rule is developed to deal with the multi-dimensional integrals. The quaternion constraint is maintained by utilizing the gain correction method. Therefore a robust strong tracking cubature Kalman filter (RSTCKF) is formed for the spacecraft attitude estimation with quaternion constraint. Unlike adopting a single fading factor in the traditional strong tracking filter, the presented filter uses two multiple fading factor matrices to make different channels have respective filter adjustment capability, which improves the tracking performance of this algorithm. Simulation results show the effectiveness of the proposed RSTCKF.

1. Introduction

Attitude estimation has drawn increasing attention over the past few years because of its widespread application in areas such as vessels, robots, aircrafts, and the spacecraft. Due to the high measurement accuracy, the attitude estimation system is often composed of the gyro and star sensor. For the quaternion nonlinear attitude model, many attitude estimation filtering algorithms have been presented to deal with quaternion constraint. These algorithms are mainly classified into the following four categories: 1) Considering that the quaternion characteristic is additive, quaternion constraint is enforced in these algorithms, such as additive extended Kalman filter [1], quaternion Kalman filter [2], norm-constrained Kalman filter [3], divided difference filter in quaternion space [4] and square-root quaternion cubature Kalman filter [5]. 2) The most typical algorithm, such as multiplicative extended Kalman filter (MEKF) [6], adopts the quaternion error to express the state variable and reduce the order of the model, which leads to an unconstrained attitude estimation model. 3) Taking into account the multiplicative property of the quaternion, the quaternion is represented as a rotating vector and combined with the filtering algorithm, such as uncorrelated unscented filter for spacecraft attitude determination [7]. 4) To avoid the problem of the quaternion constraint, the quaternion is converted to an unconstrained three-component vector. In [8], the proposed USQUE algorithm transforms the quaternion into the modified Rodrigues parameters. Among those literature, the gain correction method based on the minimum mean square error estimation [3], which is optimal in nature, has been confirmed to be an effective

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way for handling the attitude estimation problem with quaternion constraints.

Besides the quaternion constraints, model uncertainties [9–11] such as the model mismatch, unknown disturbance and status mutation, are inevitably encountered in the attitude estimation system due to the influence of complex environment. However, the aforementioned attitude estimation algorithms [1–8] are all based on accurate attitude estimation models. If there exist uncertainties in the model, the estimation performance will be degraded, even resulting in the divergence of the filter. Therefore, in the presence of model uncertainties, there is great need to develop a nonlinear attitude estimation algorithm which is much less sensitive to them, so that the estimation performance and robustness of the system can be improved. It is worth mentioning that a typical improved extended Kalman filter-strong tracking EKF presented in [12] is capable of providing strong robustness against model uncertainties including model mismatch, unknown disturbance and status mutation. The authors in [13] combine unscented Kalman filter (UKF) [14] with the strong tracking method, and propose a novel sampling strong tracking nonlinear unscented Kalman filter used in eye tracking. In [15], a strong tracking filter and wavelet transform are developed to enhance the estimation accuracy, the tracking ability and robustness of UKF, which leads to an adaptive UKF. For nonlinear networked systems with parameter perturbations as well as unknown inputs, a networked strong tracking filtering has been designed in [16]. The authors in [17] have proposed a universal nonlinear filter for maneuver targets tracking case by introducing the idea of a strong tracking filter into square-root cubature Kalman filter. All of the above strong tracking filtering algorithms simply introduce a single fading factor to adjust the prediction covariance matrix, which makes each filter channel share the same fading rate. Although the tracking capability of these algorithms has been reported, the robustness and optimal estimation performance would still be affected in the case where each filter channel has the same fading rate. To this end, the authors in [18,19] introduce one multiple fading factor matrix to alter the prediction covariance matrix. But the symmetry characteristics of the original matrix cannot be guaranteed and remain as an issue. The authors in [20] use two multiple fading factors to adjust the covariance matrix. Their algorithm, however, is based on the linear systems and cannot be directly extended to the nonlinear systems. Aiming to solve these two issues, a valid and feasible solution for the nonlinear attitude estimation system will be developed.

In this paper, for the nonlinear attitude estimation system, a three degrees spherical-radial cubature rule [21] is employed to compute the multi-dimensional gauss integrals. Then, two multiple fading factors instead of a single fading factor are used to adjust the prediction covariance matrix, which makes each filter channel have different adjustment ability and ensures the symmetry of the prediction error covariance matrix. In addition, the gain correction method is adopted to meet the quaternion constraint condition. Finally, a robust strong tracking cubature Kalman filter (RSTCKF) is formed for the spacecraft attitude estimation with quaternion constraint.

The remainder of this paper is organized as follows. In Section 2, the attitude estimation model is shown. Then, in Section 3, we provide an introduction to the problem formulation about nonlinear systems with quaternion constraints and model uncertainties. In Section 4, the feasibility of our method is analyzed. And the calculation of multiple fading factors and the filtering gain are given in detail. Section 5 carries out the four different cases with model uncertainties, such as state mutation, large initial errors, model mismatch and unknown disturbances, to verify the performance of our proposed algorithm. In Section 6, some conclusions are drawn.

2. Attitude estimation model

2.1. Gyro model

A rate-integrating gyro is used to measure the angular rate. For this gyro, a generally used three-axis continuous model is given by [22]

$$\tilde{\boldsymbol{\omega}}(t)=\boldsymbol{\omega}(t)+\boldsymbol{\beta}(t)+\boldsymbol{\eta}_v(t)$$
$$\dot{\boldsymbol{\beta}}(t)=\boldsymbol{\eta}_u(t) \quad (1)$$

where $\tilde{\boldsymbol{\omega}}(t)$ is the gyro measured angular rate; $\boldsymbol{\beta}(t)$ is the gyro bias; $\boldsymbol{\omega}(t)$ is the true angular rate; $\boldsymbol{\eta}_v(t)$ and $\boldsymbol{\eta}_u(t)$ are independent Gaussian white-noise processes with zero means and covariances σ_v^2 and σ_u^2, respectively.

2.2. Process model

According to [22], the attitude kinematics is given as

$$\dot{\boldsymbol{q}}=\frac{1}{2}\begin{bmatrix}\boldsymbol{\omega}\\0\end{bmatrix}\otimes\boldsymbol{q}=\frac{1}{2}\boldsymbol{\Omega}(\boldsymbol{\omega})\boldsymbol{q}=\boldsymbol{\Xi}(\boldsymbol{q})\boldsymbol{\omega} \quad (2)$$

where the attitude quaternion is denoted as $\boldsymbol{q}=\begin{bmatrix}q_1 & q_2 & q_3 & q_4\end{bmatrix}^T=\begin{bmatrix}\boldsymbol{\rho}^{\boldsymbol{T}} & q_4\end{bmatrix}^T$;
$\boldsymbol{\omega}=\begin{bmatrix}\omega_1 & \omega_2 & \omega_3\end{bmatrix}^T$is gyro angular rate; $\boldsymbol{\rho}$ is the quaternion vector; q_4 is the quaternion scalar part; $\otimes$ is the quaternion product; $\boldsymbol{\Omega}(\boldsymbol{\omega})$ and $\boldsymbol{\Xi}(\boldsymbol{q})$ can be defined as

$$\boldsymbol{\Omega}(\omega)=\begin{bmatrix}-[\boldsymbol{\omega}\times] & \boldsymbol{\omega}\\-\boldsymbol{\omega}^T & 0\end{bmatrix},\boldsymbol{\Xi}(\boldsymbol{q})=\begin{bmatrix}q_4\boldsymbol{I}_{3\times3}+[\boldsymbol{\rho}\times]\\-\boldsymbol{\rho}^T\end{bmatrix} \quad (3)$$

where $[\boldsymbol{\omega}\times]$ is a cross-product matrix defined by $[\boldsymbol{\omega}\times]=\begin{bmatrix}0 & -\omega_3 & \omega_2\\\omega_3 & 0 & -\omega_1\\-\omega_2 & \omega_1 & 0\end{bmatrix}$.

Suppose that the state vector is composed of the attitude quaternion $\boldsymbol{q}(t)$ and the gyro bias $\boldsymbol{\beta}(t)$, $\boldsymbol{x}(t)=\begin{bmatrix}\boldsymbol{q}(t)^{\boldsymbol{T}} & \boldsymbol{\beta}(t)^{\boldsymbol{T}}\end{bmatrix}^{\boldsymbol{T}}$. Thus, a nonlinear continuous state equation with quaternion is established as

$$\dot{\boldsymbol{x}}(t)=\begin{bmatrix}\dot{\boldsymbol{q}}(t)\\\dot{\boldsymbol{\beta}}(t)\end{bmatrix}=\begin{bmatrix}\frac{1}{2}\boldsymbol{\Omega}(\boldsymbol{\omega}(t))\cdot\boldsymbol{q}(t)\\\boldsymbol{\eta}_u(t)\end{bmatrix}=\begin{bmatrix}\frac{1}{2}\boldsymbol{\Omega}(\tilde{\boldsymbol{\omega}}(t)-\boldsymbol{\beta}(t)-\boldsymbol{\eta}_v(t))\cdot\boldsymbol{q}(t)\\\boldsymbol{\eta}_u(t)\end{bmatrix}$$