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Brief paper

Robust state estimation and its application to spacecraft control[☆]

Naeem Khan[a,1], M. Irfan Khattak[a], Dawei Gu[b,2]

[a] University of Engineering and Technology, Peshawar (Campus III, Bannu), Pakistan

[b] University of Leicester, Leicester, LE1 7RH, United Kingdom

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ABSTRACT

In this paper the estimation and attitude control problem of a rigid body spacecraft system with loss of observation is addressed. While a number of estimation algorithms are widely utilised in real-time applications, most of them are inadequate in the event of loss of observation as they are fundamentally based on the plant dynamics relying heavily on the measured output data. To overcome this shortcoming, a compensated closed-loop estimation algorithm is suggested in this work and is implemented in a spacecraft system with intermittent measured signals. The compensated observation signal, reconstructed using a linear prediction subsystem, is supplied at the measurement update step in the Kalman filtering. To limit the number of observations utilised in the linear prediction filter, a minimum mean square error based scheme is provided to obtain the size of linear prediction filter order. A Lyapunov-stability based output feedback control scheme is employed for the stabilisation problem. The simulation results demonstrate the effectiveness of the compensated algorithm wherein the aim is tackling the estimation problem subject to loss of measurements for the spacecraft application.

1. Introduction

Attitude estimation is one of the vital tasks within aeronautical applications and is carried out effectively using different configurations of sensors, e.g. accelerometers or inclinometers, gyroscopes, magnetometers and star trackers, to name but a few. The use of these measurement devices depends on the application for which they are applied (Wertz, 1990). For example, during the low acceleration phase, accelerometers are adopted for most of the robotics applications for the determination of attitude parameters (Ellery, 2000). For autonomous hovering systems (i.e. helicopters) that are capable of performing vertical take-off or landing, both high and low accelerometers are used for estimating the attitude (Pflimlin, Soueres, & Hamel, 2004).

While many estimation algorithms, including linear and nonlinear Kalman filtering, have been introduced in the literature (Anderson & Moore, 1979; Joseph, Kasper, & Arthur, 1974; Kailath, 1968; Simon, 2006; Zarchan, 2005) and a significant number of them are implemented in real-time applications (Grewal & Andrews, 2008; Kodrić, 2010) they are prone to fail in the event of a loss of observation due to their extensive reliability on the measured output data (Kar, Sinopoli, & Moura, 2012; Khan, Fekri, & Gu, 2010a,b; Sinopoli et al., 2004). In many cases, measurement losses may lead to catastrophic and disastrous effects, such as loss of human life, economic collapse and environmental pollution (Heemink & Segers, 2002). To overcome such shortcomings, it is important to design an estimation algorithm which is robust to observation losses. It should be noted that "robustness to loss of observation" is a necessary condition (but not sufficient) for being fault-tolerant to sensor failures. In other words, an estimator, which is designed to be fault-tolerant to sensor failures, may still crash in the event of full observation loss. Therefore, it remains an open problem to perform the system state estimation when sensors are not providing any measured data for a limited period of time. It is also worthwhile to emphasise that the problem of loss of output data is of significant interest in applications wherein output feedback control systems effectively rely upon the measured output signals. Hence, it is a challenging task to perform a precise estimation of the output in the event of measurement loss in the output feedback control systems that are used in a number of applications.

The spacecraft dynamics mostly rely on ground-based data processing and communication, where delay is inherent in calculations/operations (Micheli, 2001; Patton, Uppal, Simani, & Polle, 2010) or even loss of data (Khan, Ahmad, & Gu, 2010). This is because there are frequently encountered scenarios where data

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E-mail addresses: nkhan@nwfpuet.edu.pk (N. Khan), M.I.Khattak@nwfpuet.edu.pk (M. Irfan Khattak), dag@le.ac.uk (D. Gu).

[1] Tel.: +92 928 613248; fax: +92 928 613267.

[2] He is also a Chutian Visiting Professor at the China Three Gorges University, Hubei, People's Republic of China.

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packets may be lost due to various reasons including physical damage, limited bandwidth of communication channels, confined memory space of buffer register and congestion of network channels. Such shortcomings may pose a considerable impact on stability and performance of the spacecraft control system. To tackle this, the previous hardware redundancy is applied in order to increase system reliability. Hardware redundancy approaches (e.g. based on duplicate, triplicate or voting schemes) (Patton & Chen, 1997) and Fault Tree Analysis (FTA) (Kladis, Economou, Tsourdos, White, & Knowles, 2009) have been consistently implemented to handle the Fault Detection and Isolation (FDI) problem in the past. However, practical limitations such as complexity, cost, weight and unreliability of added components by the hardware along with other tradeoff concepts have turned the engineering community's attention towards Model-based FDI (MBFDI) approaches, e.g. Simani, Fantuzzi, and Patton (2003) and references therein. MBFDI approaches can circumvent the limitations of the hardware redundancy methods by using mathematical models of the plant to make appropriate decisions.

In the event of loss of observation (LOOB), a robust state estimation algorithm is required which could provide improved and optimal attitude estimation with bounded errors. In this study, the theoretical implementation of a robust estimation technique, proposed in Khan et al. (2010a,b) is discussed for the attitude estimation of a rigid body spacecraft model subject to intermittent observation losses where a Kalman filter ensures real-time estimation of the roll, pitch and yaw attitudes. The majority of the previous studies have considered obtaining the spacecraft attitude state vector by merely employing its kinematic equations – see e.g. Crassidis and Landis Markley (1996); Tongyue, Zhenbang, Jun, Wei, and Wei (2006); Heredia and Ollero (2009); Lefferts, Markley, and Shuster (1982); Pirmoradi, Sassani, and de Silva (2009) and the references therein. In this paper, both kinematic and dynamics models are considered to compute the state vector of the spacecraft model. For simplicity, model uncertainties such as distribution of momentum due to the use of rotating instruments are neglected in this analysis. This is due to the fact that this paper is mainly focused on estimation, rather than control. However, in order to illustrate some of the results, it is required to build a stable closed-loop system. To this end, an output feedback controller is designed through Lyapunov theory for the stabilisation of the spacecraft dynamics. The effectiveness of the compensated closed loop algorithm for a nonlinear rigid body spacecraft model subjected to output data loss is demonstrated through simulating a numerical example.

The remainder of the paper is organised as follows. In Section 2, the nonlinear attitude model of a rigid body spacecraft system is formulated by employing Euler equations of rotational dynamics and kinematic equations in the Modified Rodrigues parametrisations. Section 3 outlines the output feedback controller design which is aimed at stabilising the nonlinear spacecraft model. An overview of the extended version of the compensated closed-loop estimation scheme with loss of observations is discussed in Section 4. Simulation results showing the performance of the robust Extended Kalman filter (EKF) for the attitude estimation under intermittent observations are presented in Section 5. Conclusions and future work are highlighted in Section 6.

2. Rigid body spacecraft dynamics

In this section, the nonlinear plant and output dynamics of a rigid body spacecraft system are presented. Due to a number of inherent limitations of the Euler angles (which includes involvement of trigonometric functions and singularity problems) and of the quaternion parametrisations (such as extra redundant element and unit norm constraint of the four quaternion elements) discussed in Lefferts et al. (1982), the Modified Rodrigues Parameters (MRPs) have recently found an elegant enhancement compared to the family of attitude parameters (Schaub & Junkins, 2003). For this reason, MRP representations are employed for the spacecraft analysis in this paper.

2.1. Spacecraft plant dynamics

The spacecraft plant dynamics of a rigid body model are usually described by its *kinematic* equations only. However, in this work the spacecraft system is modelled as a rigid body and its state vector is described by two sets of equations namely Euler equations of rotational dynamics and the kinematic equations using MRP, to explore the complete insight of the spacecraft systems as follows:

2.1.1. Kinematic equations

According to Schaub and Junkins (2003), the kinematic equations of the rigid body spacecraft in terms of MRP are given as

$$\dot{\sigma} = \mathbf{T}(\sigma)\overline{\omega} \tag{1}$$

where σ is the MRP attitude vector and $\mathbf{T}(\sigma)$ is the Jacobian matrix defined as

$$\mathbf{T}(\sigma) = \frac{1}{2}\left[\left(\frac{1-\sigma^T\sigma}{2}\right) I_{3\times 3} + \mathbf{S}(\sigma) + \sigma\sigma^T\right]. \tag{2}$$

$\mathbf{S}(\sigma)$ is a skew symmetric matrix representing the cross product operation of vector σ, and $\overline{\omega}$ is the noisy angular velocity vector where σ and $\overline{\omega} \in \mathbb{R}^3$. Since the gyroscope output, $y_i(t)$, is proportional to the angular velocity, the following equation represents the noisy gyroscope model (Wertz, 1990):

$$y_i = a_i\dot{\theta}_i(t) + n_i(t) \quad i = 1, 2, 3 \tag{3}$$

where a_i is the scale coefficient, θ_i is the angular position, and n_i represents gyroscope noise containing the scale factor error and drift. To obtain the angular position, the output of the gyroscope (angular velocity) is required to be integrated. Such integration could potentially end up with signal divergence in time due to unmeasured noise and/or numerical integration errors. Thus it is common practice that a reference sensor is usually required to reset the gyroscope from time to time. The gyroscope noise is assumed to be Gaussian zero-mean white noise, i.e.

$$n_i \sim N(0, \Lambda) \tag{4}$$

where the intensity Λ is the variance of the noise.

2.1.2. Dynamical equations

Euler's equations of a rotational dynamics are represented by

$$\mathbf{J}\dot{\overline{\omega}} = -\mathbf{S}(\overline{\omega})\mathbf{J}\overline{\omega} + \tau \tag{5}$$

where $\tau \in \mathbb{R}^3$ is the control input torque, $\mathbf{J} \in \mathbb{R}^{3\times 3}$ is the inertia matrix and $\mathbf{S}(\overline{\omega}) = \overline{\omega} \times \overline{\omega}'$ is the skew symmetric matrix representing the cross product operation as

$$\mathbf{S}(\omega) = \begin{bmatrix} 0 & -\omega_3 & \omega_2 \\ \omega_3 & 0 & -\omega_1 \\ -\omega_2 & \omega_1 & 0 \end{bmatrix}. \tag{6}$$

The *kinematic* and *dynamic* equations (1) and (5) produce the augmented state vector associated with the plant model

$$\dot{x}(t) = f(x(t), \tau(t), \xi(t)) \tag{7}$$

where $x = [\sigma\ ,\ \omega]^T$ and ξ are the states and process noise vector.