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Recovery of information through linear prediction technique in attitude estimation of spacecraft systems

Naeem Khan [a,*], Latif Ullah Khan [a], M. Irfan Khattak [a], M. Shafi [a], Nasim Ullah [a,b]

[a] Electrical Engineering Department, UET Peshawar, Pakistan
[b] City university of Science and Information Technology, Peshawar, Pakistan

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ABSTRACT

Loss of information has become a severe phenomenon in many processes including state estimation. State (attitude) estimation plays an important role in a spacecraft system. This paper proposes a novel method to determine attitude parameters based on linear prediction technique. The proposed scheme successfully recovers the lost information based on previous information samples. This scheme is compared with the standard existing technique (Open-loop Kalman filtering) thoroughly. The Normal Equation scheme has outperformed the Open-loop scheme but is computationally costly. The simulation results are deduced using a numerical nonlinear spacecraft attitude dynamic model.

1. Introduction

State estimation under noisy environment is a wide area in numerous field of studies. In past, various theoretical work has been performed to achieve this goal. This includes Least Square Estimation (LSE), Minimum Mean Square Estimation (MMSE), Maximum a Posteriori (MAP) and others for both linear and nonlinear systems. Since, most of the studies begin with linear case of study, for such reasons Kalman filter – an optimal algorithm, is abundantly used in literature.

The working principal of Kalman filter can best be understand in two steps; time update step and measurement update step. The time update step depends on the system model while the measurement (or information) update step depends on information or data arrival. The final estimation results is based on this information received. Hence, it would be critical for Kalman filter to produce optimal results if information is uncertain or unavailable for sufficient period of time.

State estimation in uncertain environments [15,9] or noisy information [30] is a broad field of communication and control theory. This is because the problem of state or parameter estimation is of paramount importance in the analysis and design of control systems [14]. The most celebrated techniques for state estimation are Kalman filtering and its adaptive forms, particle filtering, and H_∞ filtering [8] etc. For a linear system, Kalman filter is an optimal approach where state of an LTI system is estimated based on an optimal Kalman filter gain.

For various reasons including understanding of system behavior, designing and implementation of an optimal control scheme, state (attitude) estimation has remained an important research topic for spacecraft control. Spacecraft systems in particular, mainly depend on data achieved and processed from the ground that ultimately results in time delay [26]. However, perfect communication is a valuable and the most desired asset in the event of fault and failure. To handle such unfavorable conditions, several techniques like hardware redundancy, including

* Corresponding author.
E-mail addresses: nkhan@nwfpuet.edu.pk, nkhan@uetpeshawar.edu.pk (N. Khan), latifullahkhan@nwfpuet.edu.pk, latifullahkhan@uetpeshawar.edu.pk (L.U. Khan), m.i.khattak@nwfpuet.edu.pk, m.i.khattak@uetpeshawar.edu.pk (M.I. Khattak), shafi@nwfpuet.edu.pk, shafi@uetpeshawar.edu.pk (M. Shafi), nasimullah@cusit.edu.pk (N. Ullah).

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duplex, triplex and voting schemes, has remained consistently adopted [25]. But issues like weight, complexity and cost of the supplementary elements in these hardware-based techniques have diverted the attention toward analytical redundancy (Model Based FDI) to overcome the aforementioned limitations [32].

A precise communication is a fundamental factor in achieving fruitful results in any control system. However, scenarios including finite gateways of networks, bounded spaces and overpopulated networks might cause the data packets to be lost. As a consequence, the spacecraft performance may be significantly degraded specially in terms of delay and failure due to any of these diverse conditions [27]. Hence the loss of information signal or output data, plays a vital role in spacecraft attitude control and remedies need to be explored in order to provide reliable state (attitude etc.) estimation.

Open-loop Kalman filtering (OLKF) is perhaps the most frequently adopted method, used to cope with information loss-situations. In this scheme, the first step of Kalman filter (KF) is considered while the 2nd step of Kalman filter is avoided since no information signal is available. This avoidance has alternatively led OLKF to a simpler structured solution. But to run KF with no information signal for an adequate interval of time is not a wiser approach as it causes diverged estimation results. The detail study of OLKF can be found in [29,3,31,8,20] and the references therein. Some of these literatures have demonstrated the associated limitations of this techniques too. It is an intense need to propose some novel techniques that could handle data-loss situations more efficiently and to overcome those limitations. For such reasons, a compensated closed-loop Kalman filtering algorithm is proposed in [17,18]. In the compensated closed-loop scheme, an accommodating information signal is reconstructed using linear prediction coding, for which one parameter is crucial to decides i.e. the order of linear prediction filter.

The present study has considered in elaborating two objectives: (a) to provide sufficient details of this recently proposed scheme and (b) the extensive study and comparison of these two state estimation schemes (Open-loop Kalman filtering and compensated closed-loop Kalman filtering) for a rigid body spacecraft system which is subjected to an induced signal-loss. A minimum mean square error based algorithm is proposed to decide the computation of linear prediction filter order. In order to provide the true and complete picture, these two schemes are compared with conventional estimation scheme (normal Kalman filtering without any signal-loss). In fact it provides a common base for the comparison.

Both rotational dynamic and kinematic equations are used to derive the state-space equations for the spacecraft system [1,21], contrary to the normal trend of using 'Kinematic equation' as discussed by Ref. [10,23,27,5,13] and the references therein.

The remaining paper is organized as follows: Section 2 presents the nonlinear model of a rigid body spacecraft system using Modified Rodrigues Parameterizations i.e MRP representation. Section 3 is devoted to a brief discussion of an existing control system design. A detailed discussion of the accommodating closed-loop Kalman filtering scheme is described in Section 4. The performance of open-loop estimation and the recently introduced accommodating estimation schemes is analyzed through a numerical case study in Section 5. The paper is concluded with suggestions for the future work in Section 6.

2. Rigid body spacecraft model

It is common to observe spacecraft analysis while employing kinematic equations and/or dynamic equations in Euler angles and quaternion parameterizations. These two parameterizations have certain limitations; nonlinear trigonometric functions and singularity issues are linked with Euler angles while a redundant element and unit constraint are associated with quaternion parameterizations. To overcome these shortcomings, Modified Rodrigues Parameters (MRPs) are utilized in this work which is found an advancement to the parameterization's family.

2.1. Spacecraft dynamics

In this paper, the rigid body spacecraft model is specified thorough spacecraft dynamic and kinematic equations using MRP's as follows:

2.1.1. Kinematic equations

In a compact form, Kinematic equations are expressed as

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

where σ is the Modified Rodrigues Parameters and $T(\sigma)$ is defined as

$$T(\sigma) = 0.5\left[\left(\frac{1-\sigma^T\sigma}{2}\right)I_{3\times 3} + S(\sigma) + \sigma\sigma^T\right] \tag{2}$$

wherein $S(\sigma)$ denotes the skew symmetric matrix defined as

$$S(\sigma) = \begin{bmatrix} 0 & -\sigma_3 & \sigma_2 \\ \sigma_3 & 0 & -\sigma_1 \\ -\sigma_2 & \sigma_1 & 0 \end{bmatrix} \tag{3}$$

The attitude vector σ and noisy angular velocity vector $\overline{\varpi}$ are of dimensions 3×1 with

$$\overline{\varpi} := \begin{bmatrix} \overline{\varpi}_1 \\ \overline{\varpi}_2 \\ \overline{\varpi}_3 \end{bmatrix} = \begin{bmatrix} \omega_1 - n_1 \\ \omega_2 - n_2 \\ \omega_3 - n_3 \end{bmatrix} \tag{4}$$

The gyroscope output model is $y_j(t)$ is selected as

$$y_j = c_j\dot{\theta}_j(t) + n_j(t) \quad \forall j = \{1, 2, 3\} \tag{5}$$

where c_j, θ_j and n_j represent the scale coefficient, the angular position and gyroscope noise respectively. The noise is assumed to be Gaussian white noise with zero mean, i.e.

$$n_j \sim \mathcal{N}(0, \Pi) \tag{6}$$

where Π is the bias variance.

2.1.2. Dynamic equations

Using Euler's equations, the dynamics are defined as