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Self-calibration rank filter for unknown dynamic inputs mitigation during the Mars powered descent phase

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ABSTRACT

Advanced navigation systems for pinpoint landing are required in the entry, descent and landing phase of future missions to Mars. To overcome the horizontal position estimation problem in the Mars powered descent phase, the inertial measurement unit, Doppler radar and surface beacon integrated navigation scheme is proposed, and a conventional filter such as an extended or unscented Kalman filter is adopted. However, in engineering practice, these conventional filters for nonlinear systems with unknown dynamic inputs may degrade or even diverge. The lack of navigation accuracy may result in a large growth of spurious navigations. To solve this problem, based on the rank filter, a self-calibration rank filter is proposed for state estimation of a nonlinear system to mitigate the effects of unknown dynamic inputs. Monte Carlo simulation results are presented to demonstrate the good performance of the self-calibration rank filter for the Mars powered descent navigation. The self-calibration rank filter not only prevents the divergence of the filtering but also significantly improves the state estimation accuracy.

Introduction

Mars exploration has been a hot research area. To date, many Mars landers from NASA have successfully landed on Mars, such as Mars Pathfinder (MPF), Opportunity, Phoenix and Mars Science Laboratory (MSL) missions. The general Mars entry, descent and landing (EDL) phase can be divided into four phases: the hypersonic entry phase, the subsonic parachute entry phase, the powered descent phase and the touchdown phase [3]. Future Mars pinpoint landing missions, such as Mars sample return, manned Mars landing and Mars base, may target scientifically interesting features. Furthermore, most preselected target sites for the key scientific goals are located at high elevations on the surface of Mars [3]. If the features are in areas surrounded by hazards, the lander must be precisely delivered from the Mars entry point to the preselected target site within 100 m through the general Mars EDL phase [20,30,31]. Thus, as the last and most vital phase of pinpoint landing, the application of the guidance and control systems in the powered descent phase should be realized. To realize pinpoint landing, the navigation performance should be improved so that the complete and accurate states of the vehicle can be offered to the guidance and control systems [27]. Therefore, performance improvement of navigation during the powered descent phase is the focus of this paper.

To improve navigation accuracy, not only accurate dynamic and measurement models but also an appropriate navigation filter algorithm is required. There have been many reports about new Mars powered descent navigation concepts and algorithms in the last decade. A NASA Mars technology program task is developing a prototype of an embedded, real-time navigation system for Mars final approach and EDL using the Mars Network's Electra ultrahigh-frequency (UHF) transceiver [4,5,23]. Mars powered descent navigation using radiometric data has also been proposed by Qin et al. [27]. Moreover, the Miniature Coherent Altimeter and Velocimeter (MACV), which provides altitude and velocity information, has been adopted to correct the inertial bias and drift and improve the performance of integrated navigation by Li et al. [22]. However, according to the research conclusions of Qin et al. [27] and Xiao et al. [32], no previously used navigation sensor or scheme can measure vehicle horizontal distance to the preselected landing target during the powered descent phase, which leads to large estimation errors in the horizontal position. In addition, all past research adopted the conventional Mars dynamic model, which is constructed by using the acceleration and angular velocity information from the IMU to free the dynamic model of the uncertain effects. However, in fact, they all omit the unknown inputs from Coriolis acceleration caused by the Mars rotation [27] and other unknown

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inputs from gravitational acceleration and wind influence [32–34]. What is worse, using IMU information will introduce the IMU unknown bias. Though gravitational acceleration unknown input has been considered by Xiao et al. [32], the unknown input model was assumed to be available. Unfortunately, this assumption is difficult to realize in engineering, especially in Mars exploration missions. Hence, the unknown dynamic inputs inevitably degrade the navigation accuracy. As a result, an appropriate navigation filter algorithm must be designed for unknown dynamic inputs during the powered descent phase.

Regarding the nonlinear system model in the powered descent phase, the extended Kalman filter (EKF) has been widely used in many areas during the last decades [9,21,23,24]. However, the EKF may become degraded or even diverge when the system model has parameter uncertainties or unknown inputs [16,18,25,28]. The unscented Kalman filter (UKF), which has been shown to be more accurate than the EKF, also suffers from this problem [29]. Recently, the rank filter (RF) has been proposed, which is better than the UKF [8]. However, it is also sensitive to model parameter uncertainties or unknown inputs.

Therefore, unknown input filters for stochastic discrete-time linear systems have gained the interest of many researchers during the last decades. Because the model of the unknown dynamic inputs is unavailable during the Mars powered descent phase, the conventional augmented state Kalman filter (ASKF) [15], two-stage Kalman filter (TSKF) [7], adaptive two-stage Kalman filter (ATKF) [17], optimal three-stage Kalman filter (OThSKF) and robust three-stage Kalman filter (RThSKF) [1] are not applicable, which are used only under the condition that the model or prior information of the unknown inputs is available. When the condition is unavailable, the unbiased minimum variance (UMV) estimation theory is insensitive to the unknown inputs. Thus, Kitanidis has formulated a UMV estimation method with unknown inputs by minimizing the trace of the state error covariance matrix under an algebraic constraint [19]. Darouach and Zasadzinski then used a parameterizing technique to derive another UMV estimator, which is an extension of the Kitanidis method [6]; however, this method must choose a matrix in the recursive process. Moreover, Darouach's filter is equivalent to Kitanidis's filter when a specific matrix is chosen [6]. A robust two-stage Kalman filter (RTSKF) equivalent to Kitanidis's filter has also been proposed by Hsieh [13]. Afterwards, Hsieh [11] developed an extended recursive three-step filter (ERTSF) to solve the addressed general unknown input filtering problem. Recently, on the assumption of no prior knowledge about the dynamical evolution of the fault and the unknown disturbances, Ben Hmida et al. [2] presented a new recursive filter for joint unbiased fault and state estimation for linear systems with unknown disturbances.

However, all methods mentioned above are suitable only for linear systems. Thus, a nonlinear version of the ERTSF, denoted as NERTSF, is proposed for a nonlinear traffic state estimation problem [14]. In this paper, the main work is to design an appropriate navigation filter algorithm for improved navigation performance with unknown dynamic inputs. Based on that, all linear methods mentioned above degrade into the RTSKF, which is equivalent to Kitanidis's filter. Furthermore, the NERTSF also degrades into an EKF-like nonlinear version of the RTSKF, named the robust two-stage extended Kalman filter (RTSEKF) in this paper, which inevitably has drawbacks including truncation errors caused by Taylor expansions and complexity Jacobi matrix calculation [10,14]. Therefore, based on the RF and RTSKF, a self-calibration rank filter (SCRF) is proposed for state estimation of nonlinear unknown systems to mitigate the effects of unknown dynamic inputs. Furthermore, integrated Doppler radar with six beams and a radio beacon is adopted as the navigation sensor to improve the horizontal position estimation accuracy [27].

The reminder of this paper is organized as follows. In Section 2, the problem of the nonlinear uncertain discrete-time stochastic system with unknown dynamic inputs is introduced. In Section 3, the RF is introduced, and then the SCRF is designed based on the RF. Section 4 mainly describes the Doppler radar and Mars beacon integrated navigation scheme with unknown dynamic inputs during the powered descent phase. In Section 5, adopting the integrated navigation scheme, the SCRF compared with the RTSEKF is used to address the unknown dynamic inputs in the simulations. Conclusions are given in the last section.

2. Problem statement

In the most engineering cases, the nonlinear uncertain discrete-time stochastic system with unknown inputs can be represented by

$$\mathbf{x}_k = f(\mathbf{x}_{k-1}) + \mathbf{B}_{k-1}\mathbf{b}_{k-1} + \mathbf{w}_{k-1} \tag{1}$$

$$\mathbf{z}_k = h(\mathbf{x}_k) + \mathbf{v}_k \tag{2}$$

where $\mathbf{x}_k$ is the $n \times 1$ state vector, $\mathbf{z}_k$ is the $m \times 1$ measurement vector, and $\mathbf{b}_{k-1}$ is the $p \times 1$ unknown inputs vector. Matrix $\mathbf{B}_{k-1}$ has the appropriate dimensions. $\mathbf{w}_k$ and $\mathbf{v}_k$ are zero mean uncorrelated Gaussian random sequences with

$$E\left[\begin{bmatrix}\mathbf{w}_k\\ \mathbf{v}_k\end{bmatrix}\begin{bmatrix}\mathbf{w}_k\\ \mathbf{v}_k\end{bmatrix}^T\right] = \begin{bmatrix}\mathbf{Q}_k & \mathbf{0}\\ \mathbf{0} & \mathbf{R}_k\end{bmatrix}\delta_{kj} \tag{3}$$

where $\mathbf{Q}_k \geq 0$, $\mathbf{R}_k > 0$ and δ_{kj} is the Kronecker delta, $\delta_{kj} = 1$ if $k = j$, or $\delta_{kj} = 0$.

The initial state $\mathbf{x}_0$ is assumed to be uncorrelated with the white noise processes$\mathbf{w}_k$and$\mathbf{v}_k$, and it satisfies

$$E[\mathbf{x}_0] = \hat{\mathbf{x}}_0$$

$$E[(\mathbf{x}_0 - \hat{\mathbf{x}}_0)(\mathbf{x}_0 - \hat{\mathbf{x}}_0)^T] = \mathbf{P}_0$$

When the unknown inputs model and the prior information of the unknown inputs are both unavailable in the nonlinear system, conventional methods, such as the two-stage extended Kalman filter (TEKF) [12] and adaptive two-stage extended Kalman filter (ATSEKF) [18], will lose their applicability. Still, the RTSEKF, UMV estimator and other methods are proposed. These methods have the same problems as the EKF. Thus, it is necessary to design a filter algorithm that overcomes these problems. Therefore, a SCRF based on the RF and RTSKF is formulated for a strong nonlinear system with unknown dynamic inputs.

3. Self-calibration rank filter

The algorithms mentioned above are mostly proposed to work with linear systems with unknown inputs. Regarding the nonlinear system with unknown inputs, using EKF technology, which is a linearized transformation technology, the relevant extended algorithms are obtained. However, the linearized transformation is reliable only when the error propagation can be well approximated by a linear function. If this condition is not met, this technology will undermine the performance of the filter or cause its estimation to diverge altogether. In addition, Jacobi matrix calculation is essential to the linearization, although the Jacobi matrix may not exist in some systems. Even if the Jacobi matrix exists, calculating it can be a very difficult and error-prone process, especially in the Mars powered descent system with high dimensions. To solve these problems, the RF, whose performance is better than that of the UKF, is adopted. Combining the RF and RTSKF, the SCRF is then formulated. The RF and RTSKF are reviewed in Sections 3.1 and 3.2, respectively. The structure of the SCRF algorithm is designed in Section 3.3.

3.1. Rank filter algorithm

For the following nonlinear discrete-time system,

$$\mathbf{x}_k = f(\mathbf{x}_{k-1}) + \mathbf{w}_{k-1} \tag{4}$$