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Nonlinear Kalman filters for aircraft engine gas path health estimation with measurement uncertainty

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This paper is concerned with nonlinear Kalman filtering approach to aircraft engine gas path analysis with measurement uncertainty. The uncertain measurements are characterized by time delay and packet dropout. The delay step of physical parameters occurs randomly, and its probability is regulated by a set of uncorrelated variables following Poisson distribution and uniform distribution. Packet dropout is caused as the data are not collected in time or data buffer overflows. The novel nonlinear Kalman filters (KFs) are developed using a multistep recursive estimation strategy with self-tuning buffer in the presence of gas path measurement uncertainty. The data buffers are introduced in the state estimator, the length of which is adaptive to the information loss level. The algorithms run recursively using the new arrival data and buffer position information. With a more effective arrangement of the collected measurements in real time, the better estimation accuracy of gas path health status is expected. Simulations involving abrupt fault and degradation datasets of aircraft engines were carried out to numerically evaluate and compare the performance of the improved nonlinear KFs with their existing KFs in the context of health estimation with time delay and packet dropout. The test results demonstrate that the proposed methodology not only reduces the computational time but also obtains a satisfactory accuracy for state estimation in the cases of engine gas path measurement uncertainty.

1. Introduction

Aircraft engines are complex mechanical systems that supply the power for aircrafts, and their reliabilities are crucial for flight safety. The engine performance deteriorates with the use life. The performance degradations can be characterized by the changes of the component efficiencies and flow capacities [1,2], which are defined by health parameters [3]. An effective maintenance schedule adapted to the level of deterioration of the engine benefits the overall safety and reduction of life cycle costs [4–6]. It is important to find a reliable way to acquire information about the engine health condition. Measurements from local sensors are employed to estimate the health parameters since the health information cannot be obtained directly. A variety of factors, such as constraints of bandwidth, time delays and packet dropouts, randomly occur on the measurement transmission network from a local sensor to the state estimator [7,8]. The sensor measurements collected might not be punctual, ordered or informationally complete, and these are attributed to the measurement uncertainty. These will reduce the state estimation accuracy, especially in a multi-sensor system like aircraft engine. Hence, the problem of state estimation with measurement uncertainty has drawn more attention in the presence for engine gas path health estimation.

The KF is a well-known state estimation technique and is widely used for gas turbine health parameter estimation [8–11]. Variants of the KFs are developed and applied for engine component and sensor fault diagnostics [8,9]. A bank of hybrid KFs was presented, which improved the fault detection rates and fault isolation rates in engine fault diagnosis applications [10,12]. Compared to linear Kalman filters, the nonlinear KF, such as the extended KF (EKF) and unscented KF (UKF) have better state estimation accuracies for gas turbine engine [9].

With the rapid development of the sensor measurement technology, more sensors are utilized to the advanced gas path health management of aircraft engines. The reliable collection of sensor measurements are vital to accurate health estimation results. However, measurement uncertainty inevitably happens, like random time delays and packet dropouts as was mentioned earlier. Besides, it is hard to achieve state estimation due to the complex operation and harsh environments in the engines. The stabilization problem with the limited number of packet losses was studied

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[13,14]. The stability computation of the random Riccati equation was addressed in the KF with observation losses [15], and the KF stability analysis was presented as Markov packet losses [16]. An optimal fusion state estimation method was discussed for multi-sensor systems with disordered measurements [17]. These studies prove the KF stability for state estimation with missing measurement.

In order to improve the KF performance, the robust KFs were reported to the state estimation for stochastic systems with random time delays and packet dropouts [18,19]. For linear discrete time-varying systems subject to a bounded uncertainty, a finite-horizon robust KF was developed wherein the sensor measurements were received via a packet delaying network [20]. A constant data buffer was introduced to the problems of delays and packet dropouts for state estimations of multi-sensor system, and it is easy to run and consumes less computational efforts [21,22]. The time delay of measurement is modeled by a Bernoulli distributed random sequence, and finite-horizon two-stage KFs are discussed [23]. The previous works listed above mainly focus on linear systems, besides the systematic analysis of nonlinear KFs has not been reported for the health estimation of gas turbine engines with sampling time delays and packet dropouts.

In this paper, novel nonlinear KFs are proposed with the multistep on-line recursive estimation and self-tuning buffer strategy for multi-sensor system. The issue of measurement uncertainty resulted from long-term time delay and packet dropout is concerned in gas path health estimation for aircraft engine. Long-term time delay is that delay time is more than the data sampling time of the system. The time delay model is built up to simulate the random delay steps and data dropouts. The previous data packages are restored in the buffers and used for the nonlinear state estimator with a multistep recursive calculation strategy. The contribution of this paper is to develop the improved nonlinear KFs algorithms with a data buffer for state estimation with measurement uncertainty, and the buffer length is tune to the reception ratio of measurements at the current time stamp. The detailed procedures of recursive buffer EKF (RBEKF) and UKF (RBUKF) and their tuning buffer are presented in the multi-sensor system. Time delay probabilities of the sensed measurements follow Poisson distribution and uniform distribution, and data package dropouts occur as the sampling delay time increases. The following research is undertaken by the authors both at Nanjing University of Aeronautics and Astronautics, Nanjing, China, and at the University of Toronto, Toronto, Canada. The systematic comparisons of the standard EKF, UKF and their improved algorithms are carried out for aircraft engine gas path health monitoring in the case of measurement uncertainty in the multi-sensor system.

2. Aircraft engine model and problem setup

A two-spool turbofan engine is studied in this paper. It includes inlet, fan, compressor, bypass, combustor, high pressure turbine (HPT), low-pressure turbine (LPT), mixer and nozzle. A nonlinear mathematical model of the engine is built on the basis of component level engine modeling theories [9,24], and it is expressed as follows:

$$\begin{aligned} x_{t+1} &= f(x_t, u_t) + w_t \\ y_t &= h(x_t, u_t) + v_t \end{aligned} \tag{1}$$

where u_t, x_t, and y_t separately denote the engine input variables, state variables, and sensor measurements at time t. The model input parameter is fuel flow W_f. The state variables of the engine include two spool speeds N_L, N_H and health parameters $\boldsymbol{h}$, $x = [N_L, N_H, \boldsymbol{h}^{\mathrm{T}}]^{\mathrm{T}}$. The nonlinear functions $f(\cdot)$ and $h(\cdot)$ represent the engine state transition function and measurement function, respectively. $w_t \in Q^n$ and $v_t \in R^m$ are uncorrelated Gaussian white noises with $E(w_i, w_j) = Q\delta_{ij}$, $E(v_i, v_j) = R\delta_{ij}$, and $E(w_i, v_j) = 0$ where $\delta_{ij} = 0$ $(i \neq j)$; otherwise, $\delta_{ij} = 1$.

The sensor measurements for engine health estimations contain the low pressure rotor speed N_L, high pressure rotor speed N_H, fan outlet temperature T_{22}, fan outlet pressure P_{22}, compressor outlet temperature T_3, compressor outlet pressure P_3, HPT outlet temperature T_{43}, HPT outlet pressure P_{43}, LPT outlet temperature T_6, and LPT outlet pressure P_6. The engine health parameter vector $\boldsymbol{h} = [SE_1, SW_1, SE_2, SW_2, SE_3, SW_3, SE_4, SW_4]^{\mathrm{T}}$ is employed to describe the engine performance degradation from the ideal condition. The elements of health parameters are defined as:

$$SE_i = \frac{\eta_i}{\eta_i^*}, \qquad SW_i = \frac{W_i}{W_i^*} \quad i = 1, \cdots, 4 \tag{2}$$

where η_i, W_i are the real efficiency and flow of the components, and η_i^*, W_i^* are their ideal values. The parameters SE_1, SE_2, SE_3, SE_4 are the efficiency coefficients of the fan, compressor, high pressure turbine and low pressure turbine, and SW_1, SW_2, SW_3, SW_4 are sequentially their mass flow coefficients.

Due to the constraints of the signal transmission network resources and harsh operating environment on the aircraft engine, sensor measurements will be time-delayed and partly lost in the process of their transmission. Various measurements received by the state estimator cannot be simultaneous and complete, or even data packs lost. In such case, the performance of nonlinear KF degrades, and sometimes filtering estimation will be divergence. Consequently, the nonlinear KFs for state estimation need to adapt to the measurement uncertainty like the time delays and packet dropouts in the multi-sensor system.

3. Health estimation method for aircraft engines

To improve the performance of state estimation, two aspects should be addressed: fulfill health estimation under incomplete information and make full use of available measurements. A data buffer is introduced in the KFs to collect the sensed time series, and the KFs run with the buffer recursively by a data filling strategy. The RBEKF and RBUKF are then presented in detail, which are combined the data buffer to conduct the lost information at each sampling step. The self-tuning buffer length method is developed at last in the involved nonlinear KFs to reduce computational efforts.

3.1. State estimation buffer

It is assumed that each channel has independent and random time delay of the network transmission in the multi-sensor system, and the number of delay steps follows the same probability distribution [25–27]. The time stamp is employed, and it is an important data flag. The sensor measurements from the local sensors are marked with time stamps, and sent to the state estimator through the network. Each sensor data received by the estimator is stored in a data buffer with constant length L $(L \geq 1)$. At time$t$, the first position in the buffer stores the data at time $t - L + 1$, and the last position stores the data at t. The sensor measurements are reordered in the positions according to their time stamps. If the delay step is no more than the buffer length, the sensor measurement will be stored in the buffer and available in the several coming steps. Otherwise, the measurement will drop out due to the buffer overflow.