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The Joint Estimation Approach of States and Parameters for Liquid Rocket Engine Health Monitoring*

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Abstract Based on a coventional Extended Kalman Filter (EKF), a sub-optimal fading factor EKF is proposed in this paper, which can be used for the joint estimation of states and parameters of nonlinear time-varying stochastic systems. It is used for health monitoring in such a complex system as liquid rocket engine. Numerical simulation result shows the proposed estimator has better properties such as convergence, real time, and dynamic tracking ability etc.. In addition, some problems connected with the joint estimation and the applicability for real plants are also discussed.

Key words liquid propellant rocket engine, fault diagnosis, fault isolation, state estimation, parameter estimation, nonlinear dynamic system

1 Introduction

For flight of manned vehicles, Fault Detection and Diagnosis (FDD) of propulsion system plays an important role in the safety and reliability of vehicles. In recent years, the health monitoring of Liquid Propellant Rocket Engine (LRE) has been paid much attention. Many kinds of FDD methods have been used in LRE monitoring system to improve the safety and reliability of propulsion system, which include such approaches as FDD based on signal processing[1], FDD based on analytical models[2],[3], and FDD based on artificial intelligent[4] *etc*.. Some achievements have also been obtained in practical application. But, in fact, for such a complex system as liquid propulsion system, fault isolation and identification are still rather difficult tasks. Effective isolation and identification methods are lacking, especially for nonlinear time-varying stochastic systems.

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For FDD of liquid rocket propulsion system, we think the methods based on analytical models including state estimation methods[3] and parameter estimation methods[4] are worth our while, despite there are some problems and troubles in application. Regarding fault isolation and identification for nonlinear systems, the parameter estimation methods seem to be superior to state estimation methods[4]. If the parameters of nonlinear systems can be accurately estimated on-line, it is very possible to adopt statistical methods to isolate faults.

In this paper, the joint estimation of states and parameters for nonlinear stochastic systems is considered, which maybe provide some valuable ideas for FDD of nonlinear systems or real complex plants. To improve the robustness of the conventional Extended Kalman Filter (EKF) on the mismatch of parameters of system models, in the section on theory and approach, a kind of suboptimal fading factor EKF is developed. Based on it, the joint estimation approach is proposed. To verify the effectiveness of such an estimator, in next section, the proposed approach is applied to the health monitoring of liquid rocket engine with turbopump feed system. Numerical simulation result is given. Finally, some related problems are discussed, and some ideas for further study are also presented.

2 Theory and approach

2.1 Suboptimal fading-factor EKF

Consider the discrete-time nonlinear dynamic system

$$\left.\begin{aligned} x(k+1) &= f(k,u(k),x(k)) + \Gamma(k)w(k) \\ y(k+1) &= h(k+1,x(k+1)) + e(k+1) \end{aligned}\right\} \tag{1}$$

where $x(k)$ represents an n dimensional state vector, $x\in R^n$, the input $u\in R^q$, the output $y\in R^m, f: R^n\times R^q\to R^m$, and $h: R^n\to R^m$ are nonlinear functions of the state, which are at least once differentiable. $w(k)$ and $e(k)$ are Gaussian white noise with statistics:

$$\left.\begin{aligned} E\{w(k)\} &= E\{e(k)\} = 0 \\ E\{w(k)e^{\mathrm{T}}(k)\} &= 0 \\ E\{w(k)w^{\mathrm{T}}(j)\} &= Q_1\delta_{k,j} \\ E\{e(k)e^{\mathrm{T}}(j)\} &= Q_2\delta_{k,j} \end{aligned}\right\} \tag{2}$$

where $E\{\ \}$ denotes the mathematical expectation, $\delta_{k,j}$ is kronecker function, and Q_1, Q_2 are positive defined matrices. Also, the initial state vector, $x(0)$, is assumed to be a Gaussian random vector with mean x_0 and covariance $P(0)$, so that

$$E\{[x(0)-x_0][x(0)-x_0]^{\mathrm{T}}\} = P(0) \tag{3}$$

$x(0)$ is also assumed to be uncorrelated with $w(k)$ and $e(k)$.

Based on the famous Extended Kalman Filter[5], a kind of suboptimal fading-factor EKF is developed, and is given with the form of recursive algorithms as follows:

$$\hat{x}(k+1|k+1) = \hat{x}(k+1|k) + K(k+1)\gamma(k+1) \tag{4}$$

$$\hat{x}(k+1|k) = f(k,u(k),\hat{x}(k|k)) \tag{5}$$

$$K(k+1) = P(k+1)H^{T}(k+1,\hat{x}(k+1|k))V^{-1}(k+1) \quad (6)$$

$$P(k+1|k) = \lambda(k+1)F(k,u(k),\hat{x}(k|k))P(k|k)F^{T}(k,u(k),\hat{x}(k|k)) + \Gamma(k)Q_1(k)\Gamma^{T}(k) \quad (7)$$

$$P(k+1|k+1) = [I - K(k+1)H(k+1,\hat{x}(k+1|k))P(k+1|k) \quad (8)$$

where

$$V(k+1) = H(k+1,\hat{x}(k+1|k))P(k+1|k)H^{T}(k+1,\hat{x}(k+1|k)) + Q_2(k+1) \quad (9)$$

$$\gamma(k+1) = y(k+1) - h(k+1,\hat{x}(k+1|k)) \quad (10)$$

$$F(k,u(k),\hat{x}(k|k)) = \left.\frac{\partial f(k,u(k),x(k))}{\partial x}\right|_{x(k)=\hat{x}(k|k)} \quad (11)$$

$$H(k+1,\hat{x}(k+1|k)) = \left.\frac{\partial h(k+1,x(k+1))}{\partial x}\right|_{x(k+1)=\hat{x}(k+1|k)} \quad (12)$$

The suboptimal fading-factor, $\lambda(k+1)$, can be gained by the following calculation with $\lambda(1) = 1$:

$$\lambda(k+1) = \begin{cases} \lambda_0, \lambda_0 \geq 1 \\ 1, \lambda_0 < 1 \end{cases} \qquad k = 1, 2, \cdots \quad (13)$$

where

$$\lambda_0 = \mathrm{trace}[N(k+1)]/\mathrm{trace}[M(k+1)] \quad (14)$$

$$N(k+1) = V_0(k+1) - H(k+1,\hat{x}(k+1|k))\Gamma(k)Q_1(k)\Gamma^{T}(k)H^{T}(k+1,\hat{x}(k+1|k)) - Q_2(k+1) \quad (15)$$

$$M(k+1) = H(k+1,\hat{x}(k+1|k))F(k,u(k),\hat{x}(k|k))P(k|k)F^{T}(k,u(k),\hat{x}(k|k))H^{T}(k+1,\hat{x}(k+1|k)) \quad (16)$$

In the equation (15),

$$V_0(k+1) = \frac{1}{k}\sum_{j=1}^{k+1}\gamma(j)\gamma^{T}(j) = \begin{cases} H(1,\hat{x}(1|0))P(1|0)H^{T}(1,\hat{x}(1|0)) & k = 0 \\ V_0(1) + \gamma(2)\gamma^{T}(2) & k = 1 \\ \frac{k-1}{k}[V_0(k) + \frac{1}{k-1}\gamma(k+1)\gamma^{T}(k+1) & k \geq 2 \end{cases} \quad (17)$$

2.2 The Joint estimation of state and parameter

Consider nonlinear time-varying stochastic system

$$\left.\begin{aligned} x(k+1) &= f(k,u(k),\theta(k),x(k)) + \Gamma(k)w(k) \\ \theta(k+1) &= g(k,\theta(k)) + w_1(k) \\ y(k+1) &= h(k+1,\theta(k+1),x(k+1)) + e(k+1) \end{aligned}\right\} \quad (18)$$

where θ denotes l dimensional time-varying parameter vector, g denotes l dimensional nonlinear function, $w_1(k)$ is assumed to be an independent, zero-mean, Gaussian white noise process with covariance Q_g. The other characteristics of system are the same as above section.

Now, to be able to acquire the estimation of state x and parameter θ, make augmenting as follows:

$$x_a(k+1) = \begin{bmatrix} x(k+1) \\ \theta(k+1) \end{bmatrix} \quad (19)$$

$$f_a(k,u(k),x_a(k)) = \begin{bmatrix} f(k,u(k),\theta(k),x(k)) \\ g(k,\theta(k)) \end{bmatrix} \quad (20)$$

$$h_a(k+1), x_a(k+1)) = h(k+1, \theta(k+1), x(k+1)) \tag{21}$$

$$w_a(k) = \begin{bmatrix} \Gamma(k) w(k) \\ w_1(k) \end{bmatrix} \tag{22}$$

$$e_a(k+1) = e(k+1) \tag{23}$$

Thus, the system (18) is equivalent to

$$\left.\begin{aligned} x_a(k+1) &= f_a(k, u(k), x_a(k)) + w_a(k) \\ y(k+1) &= h_a(k+1, x_a(k+1)) + e_a(k+1) \end{aligned}\right\} \tag{24}$$

Clearly, the equations (24) have the same mode as the given equation (1). Therefore, the joint estimation of state x and parameter θ can be obtained by the suboptimal fading-factor EKF.

In some cases, perhaps the joint estimation of all parameter θ and state x can not be obtained. The reason is that all parameters and states are not all identifiable. In application, this problem can be solved by experiment, that is, with the consistency of identification as decision criterion, to add gradually the amount of parameter identified together with state x at the same time.

Usually, $g(k, \theta(k))$ is unknown. In this case, it is feasible to assume $g(k, \theta(k)) = \theta(k)$ in first approximation. So, based on the equations (24), the joint estimation of the state and parameter for the system (18) can still be obtained by the suboptimal fading-factor EKF.

3 Application

Considering the health monitoring for liquid rocket engine with turbopump feed system[3], we apply the proposed estimator to the joint estimation of the state and parameter of liquid rocket engine system, so as to be able to track changes in a few selected parameters of the engine, which might be affected by the fault occurred.

Based on the nonlinear models given in reference[3], taking on-line measurable parameters including combustion chamber pressure (p_c), turbopump shaft speed (n), engine oxidizer mass flowrate (m_o), and engine fuel mass flowrate (m_f) as the engine system outputs and pressures at inlet of fuel and oxidizer pump (p_{ipf} and p_{ipo}) as the inputs, and taking the estimated parameter R_{oc} as a simulation example, which is not obtained by measuring, the nonlinear dynamic models are denoted by the following set of continuous-time equations

$$\left.\begin{aligned} \dot{x}(t) &= f(t, u(t), \theta(t), x(t)) \\ \dot{\theta}(t) &= g(t, R_{oc}(t)) \\ y(t) &= h(t, \theta(t), x(t)) \end{aligned}\right\} \tag{25}$$

The discrete-time nonlinear stochastic system models are given by

$$\left.\begin{aligned} x(k+1) &= f(k, u(k), \theta(k), x(k)) + \Gamma(k) w(k) \\ \theta(k+1) &= g(k, R_{oc}(k)) + w_1(k) \\ y(k+1) &= h(k+1, \theta(k+1), x(k+1)) + e(k+1) \end{aligned}\right\} \tag{26}$$

In simulation, time stepsize $\Delta\tau = 1ms$, and Q_1, Q_2 are taken as a constant diagonal matrix. Process noise in estimator is taken as three dimensional vector. Let $g(k, R_{oc}(k)) = R_{oc}(k)$. Q_g is also taken as a constant by experiment. The measurements y are obtained from the simulation of transient performance under fault conditions based on the full order nonlinear dynamic models of liquid rocket engine, in which the measurements obtained include measuring noise but not process noise. If necessary, see reference [5] for further details. Thus, it is clear that $x \in R^{11}, u \in R^2, \theta \in R^1, y \in R^4$, nonlinear functions $f: R^{11} \times R^2 \to R^{11}$, and $h: R^{11} \to R^4$.

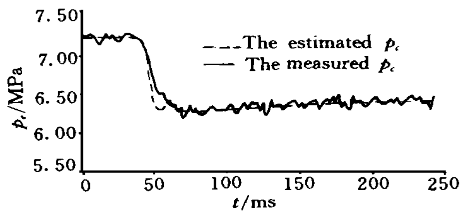

Fig. 1 The joint estimation result of combustion chamber pressure

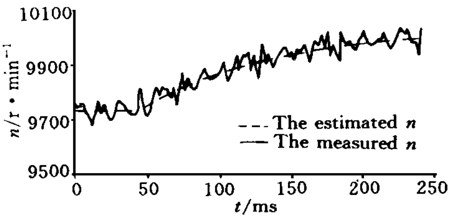

Fig. 2 The joint estimation result of turbopump shaft speed

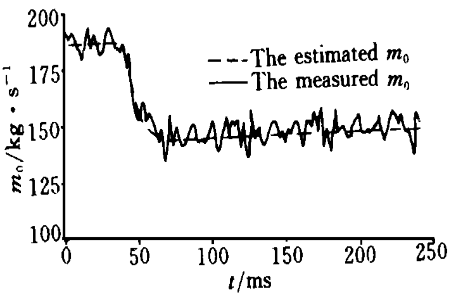

Fig. 3 The joint estimation result of engine oxidizer mass flowrate

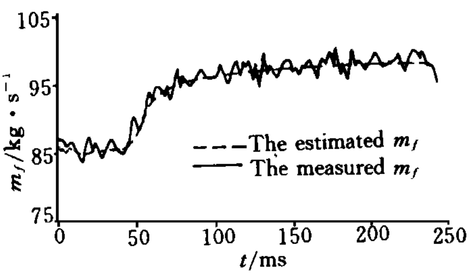

Fig. 4 The joint estimation result of engine fuel mass flowrate

The results of the joint estimation are shown in Fig. 1~Fig. 5 when fault has occurred at time $k = 40$ due to engine oxidizer main valve failure (that is, R_{oc} has changed). It is very clear that the state and parameter can be obtained the consistent estimation by the suboptimal fading-factor EKF. In the simulation, such a result can not be obtained by the conventional EKF.

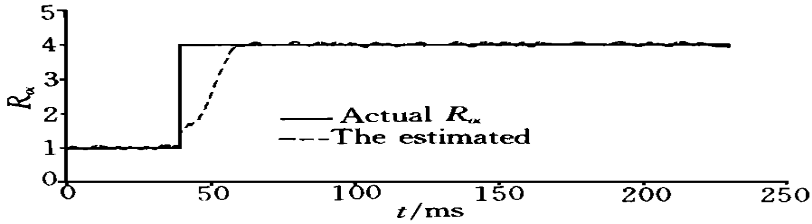

Fig. 5 The estimation result of the parameter R_∞

(at $k = 40$, failure occurs at the oxidizer main valve)

4 Conclusions

This paper proposes a kind of suboptimal fading-factor EKF, which can be used in the joint estimation of states and parameters for a class of nonlinear stochastic systems. Numerical simulation result gained in application to LRE system shows this estimator has the ability of rapidly tracking the time-varying state and parameter. In the paper, the algorithm has been given with the discrete recursive formulations, thus it is easy realized and has strong real-time operating ability. Some theoretical problems such as the identifiability of the studied system, the stability of the suboptimal fading-factor EKF *etc.* need further study.

For such a complex system as liquid rocket propulsion system, the estimations of fault isolation and fault extent are still very difficult. So far, it seems to be short of effective methods. In the paper, applying the estimator proposed to the health monitoring of LRE is only preliminary. Besides the problems mentioned above, the others such as LRE models, computational cost, estimated parameters selecting *etc.* still need much effort. But we believe that the joint estimation of states and parameters at least provides some valuable ideas for the health monitoring of liquid rocket propulsion system. Also, we think that the joint estimation approach together with knowledge engineering techniques and/or evidential reasoning methods[4],[6] may be more promising for fault diagnosis of real plants.

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状态—参数联合估计方法及其在液体火箭发动机健康监控中的应用

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摘　要　基于传统的扩展卡尔曼滤波器 (EKF)，本文提出了一种带次优渐消因子的 EKF 用于非线性时变随机动态系统状态与参数的联合估计。应用于液体火箭发动机健康监控算法的仿真研究表明，本文所提出的联合估计器具有较好的收敛性、实时性和动态跟踪能力。此外，文中还讨论了联合估计器应用于实际系统的有关问题。

关键词　液体推进剂火箭发动机，故障诊断，故障隔离，状态估计，参数估计，非线性动态系统

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