ISA Transactions 68 (2017) 327–334

Contents lists available at ScienceDirect

ISA Transactions

journal homepage: www.elsevier.com/locate/isatrans

Research article

Fault prediction for nonlinear stochastic system with incipient faults based on particle filter and nonlinear regression

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ARTICLE INFO

Article history:
Received 18 July 2016
Received in revised form
25 January 2017
Accepted 22 March 2017
Available online 2 April 2017

Keywords:
Fault detection
Fault prediction
Nonlinear stochastic system
Incipient fault
Particle filter
Nonlinear regression

ABSTRACT

This paper is concerned with the fault prediction for the nonlinear stochastic system with incipient faults. Based on the particle filter and the reasonable assumption about the incipient faults, the modified fault estimation algorithm is proposed, and the system state is estimated simultaneously. According to the modified fault estimation, an intuitive fault detection strategy is introduced. Once each of the incipient fault is detected, the parameters of which are identified by a nonlinear regression method. Then, based on the estimated parameters, the future fault signal can be predicted. Finally, the effectiveness of the proposed method is verified by the simulations of the Three-tank system.

1. Introduction

In order to keep the safety and reliability of the modern complex system, and with the development of digital computers and the system identification techniques, the design and analysis of the model-based fault detection (FD) algorithms has received considerable attention in recent decades [1–3].

As an important branch of the FD technology, FD based on stochastic models has also been well studied. For linear stochastic system (LSS), the mainly FD algorithm is by using the innovation (residual) generated by Kalman filter (KF), where the fault are detected by the statistic testing on whiteness of the residual [4,5] or by the generalized likelihood ratio (GLR) testing on the residual [6]. In order to isolate the fault, the multiple KF method is proposed in [7], where each KF is designed for detecting a specific fault. Once a fault does occur, all filters except the one has the correct hypothesis will generate the large estimation error, hence the specific fault can be isolated. For nonlinear stochastic system (NSS), the FD algorithm is similar to that of the LSS, the difference is that the KF is replaced by extended Kalman filter (EKF), unscented Kalman filter (UKF) or particle filter (PF) according to the difference assumption of the system and noise [8–10].

With the development of the FD technology, researchers begin to explore the algorithm of incipient fault detection. In [11], the on-line approximation method is proposed to detect the incipient fault, where the evolution of the incipient fault is expressed as a nonlinear function with unknown parameters. This expression about incipient fault has been cited by many literatures, such as [12–14]. In [15], a sliding-mode observer is proposed to reconstruct the incipient sensor fault. The similar method can also be used in [16] to detect and isolate the incipient sensor fault for the uncertain nonlinear system and in [17] for the quadrotor helicopter attitude control system. Owing to its wide application in fault tolerant control, fault estimation (FE) has also been noticed and some meaningful results have been achieved [18]. In [19], a multi-constrained full-order fault estimation observer (FFEO) design with finite frequency specifications was proposed. Later, this result was extended to the discrete-time systems [20], and an reduced-order fault estimation observer (RFEO) design was also obtained. It should be noted that, the incipient fault often changes slowly and it is almost unnoticeable during its early stage, hence the research on detection and estimation of the incipient fault is still a challenge problem, especially in the nonlinear systems with stochastic noise.

Meanwhile, with the improvement of requirement of the safety and reliability, researchers not only want to be able to detect the incipient fault after it occurs, but even more hope to predict the trend of the fault. If the incipient fault is detected in time and then its trend can be predicted as early as possible, then the manager will have more time to take action to avoid the possible serious

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http://dx.doi.org/10.1016/j.isatra.2017.03.018

damage. Moreover, fault prediction can also provide more support for system management and maintenance [21]. Therefore, the study about fault prediction technology has an important theoretical significance and application values. However, very few results are related to the issue of fault prediction since it is difficult to detect the incipient fault in time.

More recently, for a class of nonlinear stochastic system with additive faults, based on modified PF (MPF), a FD algorithm which can simultaneously estimate the fault and state is proposed [22]. The error of the fault estimation is closely related to the system noise and measurement noise. Theoretically, if the intensity of the system noise and measurement noise are small enough, then the accuracy of the estimated fault will be high enough. Once the estimated fault with enough accuracy is obtained, it can be used to estimate the fault's parameters, then the future fault can be predicted. However, in practice, the intensity of the system noise or measurement noise may not always sufficiently small, instead in most cases we should enlarge the system noise to compensate for modeling errors, so the MPF algorithm can not provide the estimated fault with enough accuracy. And in the case of large error of the fault estimation, it is hard to detect the fault in time, not to mention to predict the fault.

In this work, an improved method is introduced to enhance the accuracy of fault estimation in the mild case, where the intensity of the noise is not exceptionally small, and the parameters of each fault is successfully estimated through the nonlinear regression, thus realize the fault prediction. As in previous literatures, the evolution function of each incipient fault is also expressed as a nonlinear function with unknown parameters. Obviously, this nonlinear function can not be directly used in the filter design because of the unknown parameters. However, as is known, the incipient fault often changes slowly, then based on this feature, a reasonable assumption about the incipient fault is introduced, i.e., the change of each fault signal between any two adjacent time steps is always bounded and small. Combine this assumption with the PF, the modified fault estimation (MFE) algorithm is derived, and then the state estimation can also be obtained. The results show that the fault estimation precision is effectively improved. Based on the MFE, an intuitive fault detection strategy is introduced. Once the fault is detected, the parameters of each component fault are identified by an effective nonlinear regression method: Gauss–Newton method (GNM). After that, the future fault signal can be predicted in light of the expression of the incipient fault and the estimated parameters. Lastly, the effectiveness of the proposed method is illustrated by the simulation of the Three-tank system.

The rest of this paper is organized as follows. Section 2 illustrates the formulation of the nonlinear dynamic system and the process of the incipient fault. Section 3 gives the details of modified fault estimation and state estimation based on particle filter. Section 4 discusses the fault detection and fault prediction algorithm. Section 5 illustrates the proposed approach by the simulation of Three tank system. Finally, some conclusions are drawn in Section 6.

2. Problem formulation

Consider the following non-linear system with incipient faults:

$$\begin{cases} x_{k+1} = g(x_k) + \Gamma(x_k)f_k + w_k \\ y_k = C_k x_k + v_k \end{cases} \tag{1}$$

where $x_k \in \mathbb{R}^n$ and $y_k \in \mathbb{R}^p$ are the state vector and measurement vector respectively. $g(x_k)$ is the system function. $f_k \in \mathbb{R}^q$ represents the incipient fault vector, $\Gamma(x_k)$ is a known distribution matrix function, C_k is the measurement matrix with compatible dimensions. The process noise $w_k \in \mathbb{R}^n$ and measurement noise $v_k \in \mathbb{R}^p$ are mutually uncorrelated white noise sequences, with known covariance matrices $Q_k \geq 0$ and $R_k > 0$ respectively. The initial state x_0 is independent of w_k and v_k with the known mean $\hat{x}_0$ and covariance P_0. In order to simplify the discussion and without loss of generality, the known input vector u_k is not included in the system model.

Remark 1. In (1), $\Gamma(x_k)$ is a matrix function about x_k, hence the fault is multiplicative. This type of fault often represents the degradation of the component. If $\Gamma(x_k)$ is not related to x_k, then the fault is additive, and additive fault usually represents the offset in actuator. Therefore, model (1) has a wide applicability.

Let f_i denotes the ith component of the fault vector, and the incipient fault f_i can be described as

$$f_{i,k} = \begin{cases} 0, \ \ 0 \leq k < \theta_{2,i} \\ a_i(1 - e^{-\theta_{1,i}(k-\theta_{2,i})}), \ \ \theta_{2,i} \leq k \end{cases} \tag{2}$$

where a_i is a known constant that represents the maximum magnitude of the ith fault; $\theta_{1,i} > 0$ is an unknown constant that represents the rate at which the fault in state x_i evolves; $\theta_{2,i}$ is the occurring time of the ith fault. The abrupt fault can also be represented by Eq. (2). For a large value of the growth rate $\theta_{1,i}$, the profile of (2) is approximate to a step function, which often models abrupt fault. However, for fault prediction, we only consider the incipient fault.

Actually, the Eq. (2) represent the evolution of the incipient fault f_i, but we do not use it to improve the accuracy of the fault and state estimation due to the unknown parameter $\theta_{1,i}$ and $\theta_{2,i}$.

In order to obtain the useful feature of the fault signal, it is reasonable to analyze (2). Before the fault occur, the amplitude of the fault signal f_i is always a constant value 0. Once the incipient fault occurs, then the fault signal will changes slowly. Hence it is reasonable to assume that the fault signal always changes slowly. That is to say, the fault signal at present step are often related to their previous step. In detail, the amplitude of each component of the fault vector f_k almost keeps unchanged or changes slowly. Then the characteristic of the fault signal can be expressed as the following assumption and we can use it to improve the fault estimation and state estimation in Section 3.

Assumption 1.

$$f_k = f_{k-1} + w^f_{k-1} \tag{3}$$

where $w^f_{k-1} \in \mathbb{R}^q$ is a virtual Gaussian white noise with covariance matrices $Q^f_{k-1} > 0$, which represents the noise intensity. The initial fault f_{-1} is 0 and the covariance is P^f_{-1}.

Remark 2. The noise w^f_k is virtual, hence it is not related to w_k and v_k. For convenient, we can choose a fixed covariance matrices, denote as Q^f. Because the fault does not always occur and the fault is incipient, it is reasonable to considered that the fault does not change or changes slowly, then a small Q^f should be choose.

It is also assumed that $rank\ C_{k+1}\Gamma(x_k) = rank\ \Gamma(x_k) = q$ for all k and x_k. This assumption is a necessary condition to ensure that the state estimation is unbiased.

Our aim is as follows:

(1) Effectively estimate the system state and the fault signal.
(2) Detect the fault and estimate the parameters of the incipient fault.
(3) Predict the trend of the fault based on the estimated parameters.