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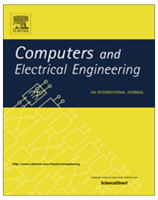

A novel approach to fault diagnosis for time-delay systems ☆

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A B S T R A C T

In this paper, a novel fault detection and identification (FDI) scheme for time-delay systems is presented. Different from the existing FDI design methods, the proposed approach utilizes fault tracking approximator (FTA) and iterative learning algorithm to obtain estimates of the fault functions. Performance of the FTA is rigorously analyzed by investigating its stability and fault tracking sensitivity properties in the presence of slowly developing or abrupt faults for state delayed dynamic systems. A novel feature of the FTA is that it can simultaneously detect and identify the shape and magnitude of the faults. Additionally, an extension to a class of nonlinear time-delay systems is made by using nonlinear control theories. Finally, the applicability and effectiveness of the proposed FDI scheme is illustrated by a practical industrial process.

1. Introduction

With the increasing demand for system safety and reliability, fault detection and identification (FDI) schemes have received more and more attention in the last two decades. Tremendous research effort has been devoted to model-based FDI methods, and many FDI schemes have been successfully applied to industrial processes. Fruitful research results can be found in some papers [1–8], and references therein.

Early FDI methods assumed the availability of an accurate system model. In practice, however, such an assumption can be invalid. The reason is that some system uncertainties and time-delay processes are always present in many complex systems, such as chemical processes, long transmission lines in pneumatic, hydraulic and rolling mill systems, which usually results in unsatisfactory performance. Therefore, robust FDI schemes that enable the detection and identification of faults in the presence of time delays and unstructured modeling uncertainties have attracted considerable attention [9–11]. For linear time-delay systems, H_∞ fault diagnosis observer provided a robust means of detecting faults from the generated residual signals [12]. Maiying Zhong [13] studied the use of robust control theory for detecting and diagnosing faults in linear time-invariant (LTI) systems. This formulation used LTI system models and requires the solution of matrix inequalities.

Compared with fruitful research results on fault detection, there were few research results on fault identification for time-delay systems. With the development of information processing technology, computer-based learning approaches were rapidly becoming an important issue in the fields of automated condition monitoring and fault diagnosis [14–18]. These approaches used computers to monitor physical system for any abnormal behavior in its dynamics using nonlinear modeling techniques. The principal design tool was a generic function approximator with adjustable parameters, referred to as on-line

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approximator. The learning methods were based on adaptive algorithms and on-line approximation structures such as neural network, fuzzy logic networks [14]. Arun et al. [15], among others, considered the construction of robust fault diagnosis architecture for a class of nonlinear systems, to detect and diagnose a sensor bias. A robust on-line estimator was proposed to detect and identify the shape and magnitude of the sensor bias, and the stability properties were rigorously investigated as well. However, within these neural network based approaches, there is no predetermined way of finding an optimum network size and architecture. Besides, in practice, updating the weights of these neural networks will be time-consuming. Any addition of new patterns cannot be accommodated easily. In [19], Chen proposed an iterative learning observer (ILO) for fault detection, estimation and accommodation. The main characteristic of the ILO was that its states were updated or driven successively by the estimation errors of previous system outputs and control inputs. Despite these promising approaches to addressing the problem of fault diagnosis in a nonlinear framework, there have not been many analytical research results on fault detection and identification for time-delay systems. Developing effective FDI algorithms for time-delay systems are becoming an issue of primary importance.

In our previous work [20], a robust fault tracking approximator (FTA) based fault detection and identification scheme for a class of nonlinear systems was developed and its stability properties were investigated. The objective of this paper is to extend the previous research results to a class of time-delay systems and investigate the stability and fault tracking properties of the FTA. We first consider linear state delayed dynamic systems, which are subject to slowly developing or abrupt faults. The key assumption is that the unstructured modeling uncertainty is bounded by a known constant in a prescribed region of interest. The main contributions of this paper are: (1) the derivation of conditions which rigorously characterize the stability and fault tracking properties of the FTA, (2) the extension to a class of nonlinear time-delay systems, (3) the computation of the fault detection threshold in the presence of unstructured modeling uncertainty.

An outline of this paper is as follows. In Section 2, the problem formulation, including the key assumptions, is described. The design of the FTA and its stability properties are investigated in Section 3. In Section 4, we extend the FTA based FDI approach to a class of nonlinear time-delay systems. A practical industrial process has been provided to illustrate the feasibility and effectiveness of the proposed approach in Section 5. Finally, in Section 6 some concluding remarks are stated.

2. Problem formulation

Let us consider a class of time-delay systems described by the following differential equations:

$$\dot{x}(t) = Ax(t) + A_d x(t-d) + Bu(t) + B_w w(t) + B_f f(t) \tag{1}$$

$$y(t) = Cx(t) \tag{2}$$

where $x(t) \in R^n$ is the system state, $u(t) \in R^p$ is the system input, $y(t) \in R^q$ is the measured system output, $w(t) \in R^h$ represents the unstructured modeling uncertainty. $f(t) \in R^p$ represents the input/output characteristics of system failure. A, A_d, B, B_w, B_f, C are known parameter matrices with appropriate dimensions. Throughout the paper, the notation $\|\bullet\|$ will be used to denote the Euclidean norm of a vector.

Assumption 1. The observability matrix associated with the pair (A, C) is full rank.

Assumption 2. The function $w(t)$ in Eq. (1), representing the unstructured modeling uncertainty, is bounded by a known constant, i.e., $\|w(t)\| \leqslant L_w$.

Remark 1. In many neural network based FDI approaches, the fault diagnosis filter was developed under the assumption that the system states were available for measurement. However, in many engineering applications, this assumption is critical and limited. Besides, there is no predetermined way of finding an optimum network size and architecture. In this paper, we will design a FTA to detect and identify system faults, which is free of these limitations.

Based on the system states Eqs. (1) and (2), we establish FTA of the forms (3)–(8):

$$\dot{\hat{x}}_k(t) = A\hat{x}_k(t) + Bu_k(t) + A_d\hat{x}_k(t-d) + L(y(t) - \hat{y}_k(t)) + B_f\hat{f}_k(t) \tag{3}$$

$$\hat{y}_k(t) = C\hat{x}_k(t) \tag{4}$$

$$e_k(t) = x(t) - \hat{x}_k(t) \tag{5}$$

$$r_k(t) = Ce_k(t) \tag{6}$$

$$\hat{f}_{k+1}(t) = \hat{f}_k(t) + \Gamma r_k(t) \tag{7}$$

$$\|y(t) - \hat{y}_k(t)\|_\infty > \gamma \qquad t \in [t_a, t_b] \tag{8}$$

where $\hat{x}_k(t) \in R^n,\ \hat{y}_k(t) \in R^q$ are estimated system states and outputs respectively. k is the iteration index. γ is the given performance index, which is used to calculate the estimation error of the system outputs. L is a pre-specified gain matrix, which makes the eigenvalues of A-LC lie in the left-half complex plan. $\Gamma \in R^{n\times q}$ is a constant gain matrix, with its elements within the scope: $(0,1)$. $\hat{f}_k(t)$ is a new introduced parameter, referred to as virtual fault, which is the estimation of $f(t)$. The initial value of $\hat{f}(t)$ is set to zero until a fault is detected. $t \in [t_a, t_b]$ and $t_b - t_a = P$. P is the iterative operation horizon. $e(t)$ denotes