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Small oscillation fault detection for a class of nonlinear systems with output measurements using deterministic learning[☆]

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ABSTRACT

Early detection of small faults is an important issue in the literature of fault diagnosis. In this paper, for a class of nonlinear systems with output measurements, an approach for rapid detection of small oscillation faults is presented. Firstly, locally accurate approximations of unknown system dynamics and fault functions are achieved by combining a high gain observer and a deterministic learning (DL) theory. The obtained knowledge of system dynamics for both normal and fault modes is stored in constant RBF networks. Secondly, a bank of dynamical estimators are constructed for all the normal mode and oscillation faults. The knowledge obtained through DL is reused with a nonhigh-gain design. The occurrence of a fault can be detected if one of residual norms of a fault estimator becomes smaller than that of the normal estimator in a finite time. A rigorous analysis of the detectability properties of the proposed fault detection scheme is also given, which includes the fault detectability condition and the fault detection time. The attractions of the paper lie in that with output measurements, the knowledge of modeling uncertainty and nonlinear faults is obtained and then is utilized to enhance the sensitivity to small faults.

1. Introduction

Developments of fault detection (FD) approaches for nonlinear systems have received more and more attention in the past decades, principally due to an increasing complexity of modern engineering systems and a higher reliability requirement. One mainstream for fault detection of nonlinear systems is model-based analytical redundancy approach (see, e.g. [1–16] and the references therein). There are various approaches for FD using analytical redundancy, such as observer based [4–6], parameter estimation based [7,8] and parity space based [9,10].

In the literature of fault diagnosis, early detection of small faults is an important issue in avoiding catastrophic consequences [3,12], and is helpful in minimization of maintenance activities and costs [17,18]. However, small faults are difficult to be detected since they may be hidden by modeling uncertainties. To solve this problem, one promising method is to use neural networks to learn the unknown system dynamics and the fault functions. In [12–14], adaptive approximation based fault diagnosis approaches have been developed, in which a fault can be detected and learned by using the measured variables. In [15], these techniques are extended to the case that the nonlinearity is modeled as a nonlinear function of the system input and state variables and satisfies a Lipschitz condition.

One key problem of learning the unknown system dynamics and fault functions is that convergence of NN weights to their optimal values requires the satisfaction of the persistent excitation (PE) condition [14,19,20]. However, the PE condition is generally very restrictive to be satisfied [14]. Recently, a deterministic learning (DL) theory was proposed for NN approximation of nonlinear dynamical systems with periodic or recurrent trajectories [21–23]. It is shown that by using localized radial basis function (RBF) neural networks, almost any periodic or recurrent trajectory can lead to the satisfaction of a partial PE condition. This partial PE condition leads to exponential stability of a class of linear time-varying adaptive systems, and accurate NN approximation of the system

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dynamics is achieved in a local region along the periodic or recurrent trajectory. Further, a DL based observer technique is presented for a class of nonlinear systems undergoing periodic or recurrent motions with only output measurements in [24]. It is showed that learning of the unknown system dynamics is achieved by combining a high gain observer and the DL techniques. The knowledge obtained through DL can be reused in state observation process to achieve a nonhigh-gain design.

Based on the DL theory, in previous works the authors develop a rapid detection scheme for small oscillation faults in the case that the measurements of all system states are available [25]. In practice, measurements of all system states may not be available. In this paper, we extend the previous results by considering a class of nonlinear systems with only output measurements. First, accurate approximation of unknown system dynamics and fault functions are achieved in a local region along the estimated state trajectory by using the DL based observer technique developed in [24]. The obtained knowledge of system dynamics for both normal and fault modes is stored in constant RBF networks.

In the diagnosis phase, a bank of dynamical estimators are constructed for all the normal mode and oscillation faults. The knowledge obtained through DL are reused with a nonhigh-gain design. The detection decision is made based on average L_1 norms of the residuals and a smallest residual principle. The occurrence of a fault can be detected if a residual average L_1 norm of the residual of a fault estimator becomes smaller than that of the normal estimator in a finite time. A rigorous analysis of the detectability properties of the proposed fault detection scheme is also given, which includes the fault detectability condition and the fault detection time. The attractions of the paper lie in that with output measurements, the knowledge of modeling uncertainty and nonlinear faults is obtained and then utilized to enhance the sensitivity to small faults.

The rest of the paper is organized as follows: Section 2 presents problem formulation and preliminary results. In Section 3, a DL-based scheme for training and rapid detection of oscillation fault modes with output measurements is presented. A rigorous analysis of the performance of the proposed detection scheme is also provided. Section 4 presents the simulation results, and Section 5 concludes the paper.

2. Problem formulation and preliminaries

2.1. Problem formulation

Consider a class of oscillation faults generated from the following class of nonlinear systems

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = x_3 \\ \vdots \\ \dot{x}_{n-1} = x_n \\ \dot{x}_n = f(x,u) + \upsilon(x,u) + \beta(t-T_0)\phi^s(x,u) + d(t) \\ y = x_1 \end{cases} \tag{1}$$

where $x \in R^n$ is the state vector of the system, $u \in R^m$ is the control input vector, $f(x,u), \upsilon(x,u), \phi^s(x,u)$ are continuous nonlinear functions, with $f(x,u)$ representing the dynamics of the nominal model, $\upsilon(x,u)$ the unknown system dynamics, and $\phi^s(x,u)$ the deviation in system dynamics due to fault s; $d(t)$ represents the disturbances. It is assumed that the disturbance is bounded such that $|d(t)| < \bar{d}$, where $\bar{d} > 0$ is a constant. $\beta(t-T_0)$ represents the fault time profile, with T_0 being the unknown fault occurrence time. When $t < T_0, \beta(t-T_0) = 0$, when $t \geq T_0, \beta(t-T_0) = 1$. The system states and inputs of (1) in normal and fault modes are referred to as the system trajectories and denoted as $\psi^0(x(t_0), u(t_0))$ and $\psi^s(x(T_0), u(T_0))$, respectively, or ψ^0 and ψ^s for conciseness of presentation.

Assumption 1. The system states and controls remain bounded in the normal and fault modes, i.e., $(x,u) \in \Omega \in R^n, \ \forall t \geq t_0$, where Ω is a compact set. Moreover, the system trajectories ψ^0 and ψ^s are in oscillations for normal and fault modes.

Assumption 2. The nonlinear terms $f(x,u)$, $\upsilon(x,u)$ and $\phi^s(x,u)$ in (1) are local Lipschitz about x uniformly for $u \in \mathcal{U}$, i.e., $\forall x, \hat{x} \in \mathcal{X}$,

$$\begin{aligned} &|f(x,u) - f(\hat{x},u)| \leq \gamma_1 |x-\hat{x}| \\ &|\upsilon(x,u) - \upsilon(\hat{x},u)| \leq \gamma_2 |x-\hat{x}|, \\ &|\phi^s(x,u) - \phi^s(\hat{x},u)| \leq \gamma_3^s |x-\hat{x}|, \end{aligned} \tag{2}$$

where γ_1, γ_2 and γ_3^s are local Lipschitz constants for $f(x,u)$, $\upsilon(x,u)$ and $\phi^s(x,u)$ in the set $\mathcal{X}$, respectively, $\mathcal{U}$ is an admissible control set, $\mathcal{X}$ is the system operation set.

The oscillation fault is "small" in the sense that

(i) the magnitude of the fault function $\phi^s(x,u)$ is allowed to be smaller than the magnitude of the modeling uncertainty $\upsilon(x,u) + d(t)$, i.e.,

$$|\phi^s(x,u)| < \bar{\eta} \tag{3}$$

where $\bar{\eta}$ is the upper bound of $\eta(x,u,t)$, $\eta(x,u,t) = \upsilon(x,u) + d(t)$;

(ii) the fault trajectory is close to the normal trajectory, i.e.,

$$dist((x,u), \psi^0) < d_\zeta, \quad \forall (x,u) \in \psi^s \tag{4}$$

where $dist((x,u), \psi^0)$ denotes the distance between the point (x,u) and the trajectories ψ^0, $0 < d_\zeta < d'_\zeta$ is a constant, and d'_ζ is the size of the NN approximation region to be given later.

2.2. Localized RBF networks and deterministic learning theory

The RBF networks belong to a class of linearly parameterized networks, and can be described by $f_{nn}(Z) = W^T S(Z) = \sum_{i=1}^{Q} w_i s_i(Z)$, where $Z \in \Omega_Z \subset R^q$ is the input vector, $W = [w_1, \ldots, w_Q]^T$ is the weight vector, Q is the NN node number, $S(Z) = [s_1(Z), \ldots, s_Q(Z)]^T$ is the vector of radial basis functions (RBFs). It has been shown (e.g. [26]) that for any continuous function $f(Z) : \Omega_Z \to R$ where $\Omega_Z \subset R^q$ is a compact set, and the RBF network $W^T S(Z)$ where the node number Q is sufficiently large, there exists an ideal constant weight vector W^* such that for each $\epsilon^* > 0$,

$$f(Z) = W^{*T} S(Z) + \epsilon(Z), \quad \forall Z \in \Omega_Z \tag{5}$$

where $\epsilon(Z) < \epsilon^*$ is the approximation error. For the bounded trajectory $Z_\zeta(t)$ within the compact set Ω_Z, $f(Z)$ can be approximated by using the neurons located in a local region along the trajectory:

$$f(Z) = W_\zeta^{*T} S_\zeta(Z) + \epsilon_\zeta \tag{6}$$

where $S_\zeta(Z) = [s_{j_1}(Z), \ldots, s_{j_\zeta}(Z)]^T \in R^{Q_\zeta}$, with $Q_\zeta < Q$, $|s_{j_i}| > \iota$, $\iota > 0$ is a small positive constant, $W_\zeta^* = [w_{j_1}^*, \ldots, w_{j_\zeta}^*]^T$, and ϵ_ζ is the approximation error, $\epsilon_\zeta = O(\epsilon)$.

Theorem 1 ([22]). *Consider any recurrent trajectory $Z(t)$. Assume that $Z(t)$ is a continuous map from $[0, \infty)$ into a compact set $\Omega_Z \subset R^q$, and $\dot{Z}(t)$ is bounded within Ω_Z. Then, for the RBF network $W^T S(Z)$ with centers placed on a regular lattice (large enough to cover the compact set Ω_Z), the regressor subvector $S_\zeta(Z(t))$, as defined in (6), is persistently exciting almost always.*

3. Training and rapid detection of oscillation faults

In this section, a DL-based scheme for training and rapid detection of oscillation fault modes with output measurement is presented. A rigorous analysis of the performance of the proposed detection scheme is also provided.