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Data-driven output-feedback fault-tolerant L_2 control of unknown dynamic systems

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ABSTRACT

This paper studies the data-driven output-feedback fault-tolerant L_2-control problem for unknown dynamic systems. In a framework of active fault-tolerant control (FTC), three issues are addressed, including fault detection, controller reconfiguration for optimal guaranteed cost control, and tracking control. According to the data-driven form of observer-based residual generators, the system state is expressed in the form of the measured input–output data. On this basis, a model-free approach to L_2 control of unknown linear time-invariant (LTI) discrete-time plants is given. To achieve tracking control, a design method for a pre-filter is also presented. With the aid of the aforementioned results and the input–output data-based time-varying value function approximation structure, a data-driven FTC scheme ensuring L_2-gain properties is developed. To illustrate the effectiveness of the proposed methodology, two simulation examples are employed.

1. Introduction

Due to the fact that it is an extremely difficult task to build qualitative and quantitative models for complex industrial plants in terms of the physical and mathematical knowledge, a class of approaches, named subspace identification methods (SIM) [1–3], has been widely investigated, which can establish the dynamics models of the plants under consideration by using the measured input–output data. For the sake of the safety and reliability of an industrial process, a great number of SIM aided data-driven fault detection and isolation (FDI) schemes have been reported over the past decade [4–7]. However, only a few literatures have involved data-driven fault-tolerant control (FTC) issues [8–13]. On the basis of the adopted key technologies, the existing data-driven FTC methods are divided into two kinds. The first one is called subspace predictive control (SPC) [11–13], which makes use of model predictive control (MPC) schemes and SIM. By means of recursive identification of the closed-loop Markov parameters of a system, the online reconfiguration of a predictive controller is implemented such that FTC is fulfilled. Ding et al. [8,9] and Yin et al. [10] proposed the second category of data-driven FTC approaches, which employed a fault-tolerant control architecture (FTCA) that was a data-driven realization of the Youla parameterization [14] of all stabilization controllers based on a residual generator. In the context of the FTCA, performance optimization was taken into account in [10], where a prescribed performance index was minimized through resorting to the iterative configuration of the parameters of a post-filter. Besides, a data-driven output-feedback FTC scheme with optimal performance was recently given in [15], which did not involve the disturbance attenuation and the tracking control issues in comparison with this work.

In recent years, approximate dynamic programming (ADP) approaches have received more and more attention [16–21]. Among these schemes, the so-called Q-learning has attracted much interest because it is a class of model-independent methods and is capable of tackling optimization problems, such as linear quadratic regulation [19], L_2-gain with state feedback [16], and tracking control [20]. Nevertheless, Q-learning requires measurement of the whole state vector, which may be expensive, difficult, or even technically impossible in certain industrial processes. To this end, output-feedback ADP algorithms were proposed in [17,18], where optimal control laws for unknown dynamic systems were given using only the measurable input–output data. The above-mentioned ADP methods are not able to deal with optimal control issues for time-varying systems owing to the time-invariant value function approximation (VFA) structure utilized by them. For this reason, [21] put forward a state-based VFA

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structure of time-varying plants. The resulting ADP algorithms address the state-feedback-based FTC problem for partially unknown dynamic systems and, however, cannot deal with the disturbance attenuation issue.

Motivated by all the researches mentioned above, this paper studies the data-driven FTC problem considering L_2-gain properties in a framework of output-feedback-based active FTC. The results of the paper have the following distinct features in comparison with the existing works:

- According to the data-driven form of observer-based residual generators, the system state is expressed in the form of the measured input–output data.
- Under the condition that full information about the internal states of unknown linear time-invariant (LTI) discrete-time plants is unavailable, the L_2 control for the plants cannot be achieved via the state-feedback-based method given in [16]; however, this task can be completed by means of the output-feedback-based approach designed in this paper.
- Different from the data-driven FTC methodologies reported in [8–13], the FTC scheme developed in this work addresses the L_2 disturbance attenuation problem for the controlled plant working in both normal and faulty cases.

The rest of this paper is organized as follows. In Section 2, the problem statement and the preliminaries are presented. Section 3 describes an output-feedback-based approach to the L_2-gain problem for unknown LTI discrete-time plants, a design method for a pre-filter to achieve tracking control and a data-driven output-feedback FTC scheme considering L_2-gain performance of unknown dynamic systems. To show the effectiveness of the proposed methods, two simulation examples are given in Section 4. Finally, Section 5 draws the conclusion.

2. Problem statement and preliminaries

2.1. System model

Suppose that the plant under consideration is modelled in the following form:

$$x_{k+1} = (A+\Delta A)x_k + (B+\Delta B)u_k + Kv_k$$
$$y_k = Cx_k \tag{1}$$

where $y_k \in \mathcal{R}^l$, $x_k \in \mathcal{R}^n$, $u_k \in \mathcal{R}^m$ and $v_k \in \mathcal{R}^o$ denote the system output, system state, control input and disturbance vectors, respectively. ΔA and ΔB stand for the changes in system dynamics caused by faults, such as plant faults [11], actuator faults including outage and partial loss of effectiveness [22–26], and so on. A, B, C, K, ΔA and ΔB are unknown matrices with appropriate dimensions. Moreover, it is assumed that the above model is controllable and observable, and that the data-driven FTC scheme designed in this work is implemented under laboratory conditions, where the measurement noise and the external disturbance are very small and therefore are neglected, and v_k can be constructed as described in Fig. 1 to find the worst case disturbance v_k^*. Thus, when carrying out the FTC scheme shown in Fig. 1, v_k is known. As a result, (1) in failure-free runs is rewritten as

$$x_{k+1} = Ax_k + [B\ \ K]\tau_k$$
$$y_k = Cx_k \tag{2}$$

where $\tau_k = \left[u_k^T\ v_k^T\right]^T$. Then, by (2), the I/O model is built up as

$$\mathcal{Y}_{k,f} = \Xi_f \mathcal{X}_k + \mathcal{H}_{f-1}\mathcal{T}_{k,f} \tag{3}$$

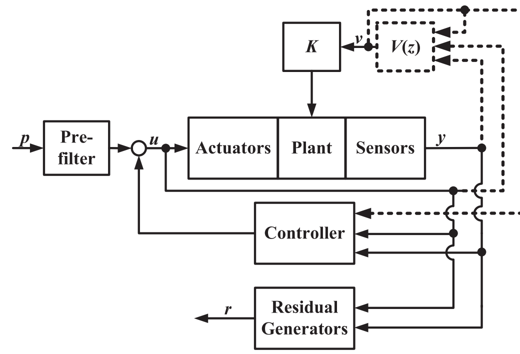

Fig. 1. Data-driven FTC scheme considering L_2-gain performance under laboratory conditions.

where

$$\Xi_f = \left[C^T\ \ (CA)^T\ \cdots\ (CA^{f-1})^T\right]^T,$$

$$\mathcal{X}_k = \left[x_k\ \ x_{k+1}\ \cdots\ x_{k+N-1}\right],$$

$$\mathcal{H}_{f-1} = \begin{bmatrix} 0 & \cdots & \cdots & 0 \\ C[B\ \ K] & \ddots & & \vdots \\ \vdots & \ddots & \ddots & \vdots \\ CA^{f-2}[B\ \ K] & \cdots & C[B\ \ K] & 0 \end{bmatrix},$$

$$\mathcal{Y}_{k,f} = \left[y_{k,k+f-1}\ \ y_{k+1,k+f}\ \cdots\ y_{k+N-1,k+N+f-2}\right],$$

$y_{k+i,k+i+f-1} = \left[y_{k+i}^T\ y_{k+i+1}^T\ \cdots\ y_{k+i+f-1}^T\right]^T$, $i = 0, \ldots, N-1$, the subscript f is greater than n and represents the future horizon, and $\mathcal{T}_{k,f}$ has the same structure as $\mathcal{Y}_{k,f}$; however, it is composed of the data set $\{\tau_i \mid i = k, \ldots, k+N+f-2\}$.

2.2. Control objective

Some fault modes of the unknown dynamic system having the form (1) are often known in practice and can be simulated in the laboratory. For this reason, it is the purpose of this paper that both the control policy with disturbance attenuation and tracking properties, and the residual generator corresponding to each of these fault modes are obtained in laboratory environments. In this work, the disturbance attenuation performance is characterized by means of the L_2-gain condition

$$\frac{\sum_{i=0}^{H}(u_i^T R u_i + y_i^T Q y_i)}{\sum_{i=0}^{H} v_i^T v_i} \le \gamma^2 \quad \forall H \tag{4}$$

where γ is an upper bound on the desired L_2-gain disturbance attenuation, $R > 0$ and $Q > 0$ are the weighting matrices prescribed in advance, $y_0 = 0$, and v_k is any disturbance whose energy is bounded.

The proposed data-driven FTC scheme is shown in Fig. 1. Note that the FTC scheme should be carried out under laboratory conditions that the sensor noise and the process noise are very small and thus are neglected.

For the sake of convenience, the parts with the dotted lines in Fig. Fig. 1 are called the module for construction of the worst case disturbance (MCWCD). Every time when a fault arising in laboratory settings is detected by a residual generator, MCWCD is enabled (i.e. let v_k be constructed through the use of the feedback element $V(z)$ and the measured input–output data). Then, both the optimal control u_k^* and the worst case disturbance v_k^* meeting (4) and corresponding to the present faulty system are achieved in terms of the proposed online learning algorithm. After that, MCWCD is disabled (i.e. v_k is set to zero). Meanwhile, based on the online data collected in the above process, a new residual