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Auxiliary Signal Design for Active Fault Detection Based on Set-membership ⋆

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Abstract: In this paper, a new active fault detection method based on set-membership is proposed. Similar to the existing methods, the normal and faulty modes of the system are assumed to be two linear discrete time-invariant systems with bounded energy uncertainty, which is represented by a bounded ellipsoid under the framework of set-membership. Then the minimal energy auxiliary signal is derived in the case with worst cases of uncertainties by adopting a geometric method, such that desired fault detection performance can be guaranteed. Note that with comparison to the existing methods, the proposed method has a clear physical meaning and the set-membership technique makes it more feasible to calculate the fault detection rates relative to different choices of auxiliary signals with smaller energy. Hence the energy of auxiliary signal can be determined by a trade off between the fault detection rate and the impact on normal operation of the system. Simulation results are provided to show the effectiveness of the proposed method.

Keywords: active fault detection, auxiliary signal design, set-membership

1. INTRODUCTION

With the increasing demands on reliability and safety in modern industrial plants, fault detection has become a vitally important topic. The existing fault detection approaches can roughly be classified into two categories (Nikoukhah et al. (2000)). One category is passive approaches (Nikoukhah et al. (2000)), with which the input and output signals of the system are monitored and a fault is decided by comparing the monitored behavior with the normal behavior of the system. In fact, most of the traditional fault detection results including Chen and Patton (1999) and Ding (2008) are obtained based on passive approaches. The second category is active approaches (Nikoukhah et al. (2000)), which use auxiliary signals (also called as test signals) to excite the systems and improve the detectability of the faults, such as Zhang (1989), Nikoukhah et al. (2000), Šimandl and Punčochář (2009) and Scott et al. (2014).

In active fault detection approaches (Esna Ashari et al. (2012b), Niemann and Poulsen (2014) and Scott et al. (2014)), system structure or parameter faults are considered. Besides, the normal and faulty modes of the system are assumed to be known and different. Similar assumptions can also be encountered in solving passive fault detection based on multiple models (Loparo et al. (1991) and Zhang and Rong (1998)). However, different from passive detection methods, the introduction of additional auxiliary signals can excite and exhibit more abnormal system behaviors. Thus more faults can be detected via active methods than passive approaches (Nikoukhah et al. (2000, 2002)). The concept of auxiliary signals was inspired from system identification (Šimandl and Punčochář (2009)), where persistently exciting signals are required. However, the persistently exciting signals may severely affect normal operation of the systems, which may not be acceptable in practice. In contrast to this, the impact of auxiliary signals in active fault detection on normal operation of the systems can be reduced at an acceptable level. This is because i) the system models in normal and faulty modes are assumed to be known a priori, thus the purpose is to distinguish different system modes instead of identifying all the system parameters; ii) the auxiliary signal is normally injected into the system on a periodic basic or at the critical times; 3) the energy of auxiliary signals is offen restricted, such as to reach its minimum value in Nikoukhah et al. (2000).

In Zhang (1989), Šimandl and Punčochář (2009) and Kim et al. (2013), active fault detection methods of stochastic systems are developed, where the probability density functions of noises are assumed to be known. In Blackmore et al. (2008), it is assumed that the switchings among different stochastic modes can be represented as a Markov jumping process. On the other hand, a number of active fault detection works are investigated based on the assumptions that the uncertainties in different system modes can be bounded by a deterministic set. In Nikoukhah et al. (2000, 2002), the normal and faulty modes of the system are modeled as two linear systems with bounded energy uncertainties. Then an optimization problem is

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constructed to derive the minimal energy auxiliary signal for guaranteed fault detection performances. Standard optimal control techniques (Bryson (1975)) are incorporated. Moreover, active fault detection methods are applicable to uncertain sample-data systems (Nikoukhah and Campbell (2005)) and nonlinear systems (Nikoukhah and Campbell (2006)), etc. In Scott et al. (2014), the uncertainties are described by zonotopes under the framework of set-membership. Then the auxiliary signal is designed by solving a mixed-integer quadratic program problem. Besides, in Poulsen and Niemann (2008) and Busch and Peddle (2014) the auxiliary signal is chosen as a single frequency periodic signal.

It should be noted that one common feature of the aforementioned methods with a priori bounded uncertainty set including Nikoukhah et al. (2000, 2002) and Scott et al. (2014) is that, the auxiliary signals are all designed for the worst cases of uncertainties to prevent misdetection. This implies that the obtained minimal energy auxiliary signal is actually quite conservative. Since the worst cases of uncertainties will occur with an extremely low possibility in practice, an auxiliary signal with even smaller energy may lead to high fault detection rate while a reduced impact on normal operation of the system.

Motivated by the idea mentioned above, a new active fault detection method for linear systems with deterministic uncertainties is proposed in this paper. Different from the existing related results including Nikoukhah et al. (2000, 2002) and Scott et al. (2014), the main advantages of our method can be summarized as follows. (i) Although the minimal energy auxiliary signal is still derived for the worst cases of uncertainties, it is more feasible than existing methods to further compute the fault detection rates corresponding to different choices of auxiliary signals with smaller energy. Thus the energy of auxiliary signals can be determined by a trade off between the fault detection rate and the impact on normal operation; (ii) In Nikoukhah et al. (2000, 2002), the minimal energy auxiliary signal is designed by solving an optimization problem. These methods assume that the normal and faulty models have the same output signals and then design an auxiliary signal that forces violating the a priori uncertainty bound under this assumption to detect the fault. As opposed to this, the minimal energy auxiliary signal is designed under the framework of set-membership in this paper. The constraint of uncertainties is represented by a bounded ellipsoid. And the output signals of normal and faulty system modes can be represented as two different ellipsoids. Then the minimal energy auxiliary signal is designed to guarantee that the two output ellipsoids have no intersections. Clearly, our set-membership based approach has a clear geometric explanation, and the optimization problem can be solved by a geometric method.

Notations: Throughout the paper, $\mathbb{N}$ denotes the set of nonnegative integers, $\mathbb{R}^n$ denotes the n dimensional Euclidean space, $\mathbb{R}^{n\times m}$ is the set of all $n\times m$ real matrices. I and $\mathbf{0}$ are the identity matrix and zero matrix with appropriate dimensions. $\emptyset$ donates the empty set. $\|\bullet\|$ is the Euclidean norm of a vector. For a real symmetric matrix X, $X>0$ denotes that X is positive definite. Any bounded ellipsoid with a nonempty interior can be represented as $\Xi(c;P)=\{x\in\mathbb{R}^n \big| (x-c)^TP^{-1}(x-c)\le 1, P>0\}$, and the size of an ellipsoid is measured by $\mathcal{M}(\Xi(c;P))=\mathbf{det}(P)$ (Durieu et al. (2001)). The affine transformation of an ellipsoid is also an ellipsoid and there is $A\Xi(c;P)+b=\Xi(Ac+b;APA^T)$. With the matrices A, B, C, D, and the symbol s (representing y,μ_i,v), the following matrices are defined similarly to Wang and Qin (2002)

$$H_N^0(A,B,C,D) = \begin{bmatrix} D & \mathbf{0} & \cdots & \cdots & \mathbf{0} \\ CB & D & \mathbf{0} & \cdots & \vdots \\ CAB & CB & D & \mathbf{0} & \vdots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ CA^{N-1}B & CA^{N-2}B & \cdots & CB & D \end{bmatrix} \tag{1}$$

$$H_{x_0,N}^0(A,C) = \begin{bmatrix} C \\ CA \\ \vdots \\ CA^N \end{bmatrix} \tag{2}$$

$$\bar{H}_N^0(A,B,C,D) = \left[H_N^0(A,B,C,D)\ H_{x_0,N}^0(A,C)\right] \tag{3}$$

$$s_N^0 = \left[s^T(0)\ s^T(1)\ \cdots\ s^T(N)\right]^T \tag{4}$$

$$x_{i,N}^1 = \left[x_i^T(1)\ x_i^T(2)\ \cdots\ x_i^T(N)\right]^T \tag{5}$$

2. PROBLEM FORMATION AND PRELIMINARY

2.1 Problem Formation

Similar to Nikoukhah et al. (2000), we consider a class of linear discrete time-invariant (LDTI) systems modeled as

$$\begin{aligned} x_i(k+1) &= A_ix_i(k)+B_iv(k)+M_i\mu_i(k) \\ y(k) &= C_ix_i(k)+D_iv(k)+N_i\mu_i(k) \end{aligned} \tag{6}$$

where $i=0$ and $i=1$ correspond to the normal and faulty modes, respectively. $x_i(k)\in\mathbb{R}^{n_{x_i}}$ is the system state, $v(k)\in\mathbb{R}^{n_v}$ is the auxiliary signal, $y(k)\in\mathbb{R}^{n_y}$ is the measured output, and $\mu_i(k)\in\mathbb{R}^{n_{\mu_i}}$ represents unknown disturbances and noises. Parameter matrices A_i,B_i,M_i,C_i,D_i,N_i are all supposed to be known with appropriate dimensions. The following assumptions are imposed.

Assumption 1. $\mu_i(k)$ and unknown initial state $x_i(0)$ satisfy that

$$x_i^T(0)x_i(0)+\sum_{k=0}^{N}\mu_i^T(k)\mu_i(k)\le 1, \quad i=0,1 \tag{7}$$

with $1\le N\in\mathbb{N}$.

Assumption 2. N_i has full row rank.

By adopting set-membership technique, the uncertainties $\bar{\mu}_{i,N}^0 \triangleq \left(x_i^T(0),\mu_i^T(0),\cdots,\mu_i^T(N)\right)^T$ in *Assumption 1* can be ensured bounded by the following ellipsoid

$$\Delta_{i,N} = \Big\{\left(x_i^T(0),\mu_i^T(0),\cdots,\mu_i^T(N)\right)^T \Big| \ x_i^T(0)x_i(0)+ \sum_{k=0}^{N}\mu_i^T(k)\mu_i(k)\le 1\Big\} \triangleq \Xi(\mathbf{0};Q_N) \tag{8}$$

with $Q_N=\mathrm{I}_{n_{x_i}+(N+1)n_{\mu_i}}$.