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Data-driven robust receding horizon fault estimation[☆]

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ABSTRACT

This paper presents a data-driven receding horizon fault estimation method for additive actuator and sensor faults in unknown linear time-invariant systems, with enhanced robustness to stochastic identification errors. State-of-the-art methods construct fault estimators with identified state-space models or Markov parameters, without compensating for identification errors. Motivated by this limitation, we first propose a receding horizon fault estimator parameterized by predictor Markov parameters. This estimator provides (asymptotically) unbiased fault estimates as long as the subsystem from faults to outputs has no unstable transmission zeros. When the identified Markov parameters are used to construct the above fault estimator, stochastic identification errors appear as model uncertainty multiplied with unknown fault signals and online system inputs/outputs (I/O). Based on this fault estimation error analysis, we formulate a mixed-norm problem for the offline robust design that regards online I/O data as unknown. An alternative online mixed-norm problem is also proposed that can further reduce estimation errors at the cost of increased computational burden. Based on a geometrical interpretation of the two proposed mixed-norm problems, systematic methods to tune the user-defined parameters therein are given to achieve desired performance trade-offs. Simulation examples illustrate the benefits of our proposed methods compared to recent literature.

1. Introduction

Model-based fault diagnosis techniques for linear dynamic systems have been well established during the past two decades (Chen & Patton, 1999; Ding, 2013). Recently, the model-based receding horizon approach has received attention because it provides a flexible framework to enhance robustness of passive fault diagnosis (Zhang & Jaimoukha, 2014) and to enable optimal input design in active fault diagnosis (Raimondo, Braatz, & Scott, 2013). However, an explicit and accurate system model is often unknown in practice. In such situations, a conventional approach first identifies the system model from system I/O data, and then designs the model-based fault diagnosis system (Manuja, Narasimhan, & Patwardhan, 2009; Patwardhan & Shah, 2005; Simani, Fantuzzi, & Patton, 2003). Without explicitly identifying a system model, recent research efforts investigate data-driven approaches to construct a fault diagnosis system utilizing the link between system identification and the model-based fault diagnosis methods (Ding, 2014; Russel, Chiang, & Braatz, 2000). Such data-driven approaches simplify the design procedure by skipping the realization of an explicit system model, while at the same time allow developing systematic methods to address the same fault diagnosis performance criteria as the existing model-based approaches.

Most recent data-driven fault diagnosis approaches for unknown linear dynamic systems can be classified into two categories. The first category, e.g., Qin and Li (2001) and Ding (2014), identifies a projection matrix known as parity space/vectors for residual generation, by exploiting the subspace identification method based on principal component analysis (SIM-PCA). However, as pointed out in Dong, Verhaegen, and Gustafsson (2012a), a model reduction step is needed to determine the projection matrix, hence leads to the nonlinear dependence of the generated residuals on the identification errors. Therefore it is difficult to guarantee

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the robustness of such data-driven methods to the identification errors.

The second category of data-driven fault diagnosis methods, e.g., Dong et al. (2012a); Dong, Verhaegen, and Gustafsson (2012b), utilizes the Markov parameters (or impulse response parameters). It first constructs residual generators parameterized by the predictor Markov parameters (MPs). Then the residual signal linearly depends on the identification errors of the predictor MPs. Hence a robust scheme can be developed to cope with stochastic identification errors.

Compared to fault detection and isolation, it is much more involved to estimate the fault signal in the data-driven setting. The work in Alcala and Qin (2009) proposed to reconstruct faults by minimizing the reconstructed squared prediction error obtained from PCA. However, this approach did not fully investigate the statistical estimation performance. The method in Dong and Verhaegen (2012) constructed system-inversion based fault estimators with the predictor MPs. Its fault estimates are asymptotically unbiased as the estimation horizon length tends to infinity, if the underlying inverted system is stable. However, it cannot be directly applied to sensor faults in an unstable open-loop plant because its underlying inverted system is unstable. Moreover, it does not compensate for the identification errors. The robustness of fault estimation to the identification errors is critical in two situations: (1) there exist large identification errors due to small number of identification data samples or low signal-to-noise ratio in identification data; (2) multiplication of the erroneous identified model with online I/O data of large amplitude cannot be simply ignored.

Motivated by the above two drawbacks of the proposed method in Dong and Verhaegen (2012), this paper develops data-driven robust fault estimation methods for additive actuator/sensor faults, utilizing the identified MPs. In order to pave the way for data-driven design, we first construct a receding horizon (RH) fault estimator parameterized by the predictor MPs, assuming that the predictor MPs are accurately available. It gives (asymptotically) unbiased fault estimates under the condition that the fault subsystem has no unstable transmission zeros. The above condition for unbiasedness generalizes the requirement of stable inversion in Dong and Verhaegen (2012). An immediate benefit is that our approach can be applied to sensor faults in unstable open-loop plants as long as the above condition for unbiasedness is satisfied, whereas the proposed method in Dong and Verhaegen (2012) cannot.

Our data-driven design parameterizes the above RH fault estimator with predictor MPs identified from data. The obtained data-driven fault estimation error is linear with regard to the stochastic identification errors of MPs, although the identification errors appear as multiplicative uncertainty that couples with unknown fault signals as well as online I/O data. In order to enhance robustness to stochastic identification errors, we propose two mixed-norm fault estimators. The first one can be designed offline by regarding the online I/O data as unknown. By exploiting online I/O data in its formulated mixed-norm problem, the second robust fault estimator further reduces estimation errors when the online I/O data have large amplitudes, at the cost of increased online computational burden. Based on a geometric interpretation of the formulated mixed-norm problems, a systematic tuning method for the user-defined parameters therein is provided to achieve the desired trade-offs between estimation bias and variance. Our proposed methods can handle sensor and actuator faults either separately or simultaneously. Only the separate scenario is illustrated in detail in this paper. Exact formulas for the simultaneous scenario can be derived in a straightforward manner but are omitted for the sake of brevity.

The rest of this paper starts with the problem formulation and some preliminaries on identification of predictor MPs in Section 2. Section 3 constructs the predictor-based RH fault estimator, and analyzes its condition for unbiasedness. A data-driven nominal fault estimator is given in Section 4. Sections 5 and 6 propose two mixed-norm fault estimators with robustness to identification errors. Simulation studies are given in Section 7.

2. Preliminaries and problem formulation

2.1. Notations

For a matrix X, its range and null space is denoted by $\mathcal{R}(X)$ and $\mathcal{N}(X)$, respectively. X^- represents the left inverse satisfying $X^-X = I$, while $X^{(1)}$ represents the generalized inverse satisfying

$$XX^{(1)}X = X. \tag{1}$$

$X^{[i]}$ represents the ith column of X. The trace of X is denoted by $\mathrm{tr}(X)$. Let $\|X\|_F$ represent the Frobenius norm of the matrix X. The minimal eigenvalue of a symmetric matrix X is represented by $\lambda_{\min}(X)$. Let $\mathrm{vec}(X)$ represent the column vector concatenating the columns of X. The symbol "$\otimes$" stands for Kronecker product. Let $\mathrm{diag}(X_1, X_2, \ldots, X_n)$ denote a block-diagonal matrix with $X_1, X_2, \ldots, X_n$ as its diagonal matrices.

2.2. Problem formulation

We consider linear discrete-time systems governed by the following state space model:

$$\begin{aligned} \xi(k+1) &= A\xi(k) + Bu(k) + Ef(k) + Fw(k) \\ y(k) &= C\xi(k) + Du(k) + Gf(k) + v(k). \end{aligned} \tag{2}$$

Here $\xi(k) \in \mathbb{R}^n$, $y(k) \in \mathbb{R}^{n_y}$, and $u(k) \in \mathbb{R}^{n_u}$ represent the state, the output measurement, and the known control input at time instant k, respectively. The process and measurement noises $w(k) \in \mathbb{R}^{n_w}$ and $v(k) \in \mathbb{R}^{n_v}$ are white zero-mean Gaussian, with covariance matrices $\mathrm{E}\left(w(k)w^{\mathrm{T}}(k)\right) = Q$, $\mathrm{E}\left(v(k)v^{\mathrm{T}}(k)\right) = R$, $\mathrm{E}\left(w(k)v^{\mathrm{T}}(k)\right) = 0$. $f(k) \in \mathbb{R}^{n_f}$ is the unknown fault signal to be estimated. A, B, C, D, E, F, G are constant real matrices with appropriate dimensions.

Assumption 1. The system (2) admits the one-step-ahead predictor form given by Kailath, Sayed, and Hassibi (2000); van der Veen, van Wingerden, Bergamasco, Lovera, and Verhaegen (2012)

$$\begin{aligned} x(k+1) &= \Phi x(k) + \tilde{B}u(k) + \tilde{E}f(k) + Ky(k) \\ y(k) &= Cx(k) + Du(k) + Gf(k) + e(k), \end{aligned} \tag{3}$$

where K is the steady-state Kalman gain, $\Phi = A - KC$, $\tilde{B} = B - KD$, and $\tilde{E} = E - KG$, $\{e(k)\}$ is the zero-mean innovation process with the covariance matrix Σ_e.

We consider additive sensor or actuator faults in this paper, i.e.,

$$j\text{th sensor fault: } E = 0_{n_x \times 1}, \qquad G = I^{[j]}, \qquad \tilde{E} = -K^{[j]}; \tag{4}$$

$$l\text{th actuator fault: } E = B^{[l]}, \qquad G = D^{[l]}, \qquad \tilde{E} = \tilde{B}^{[l]}; \tag{5}$$

with $X^{[j]}$ representing the jth column of a matrix X.

Denote the predictor MPs by

$$H_i^u = \begin{cases} D & i = 0 \\ C\Phi^{i-1}\tilde{B} & i > 0 \end{cases}, \qquad H_i^y = \begin{cases} 0 & i = 0 \\ C\Phi^{i-1}K & i > 0 \end{cases},$$
$$H_i^f = \begin{cases} G & i = 0 \\ C\Phi^{i-1}\tilde{E} & i > 0. \end{cases} \tag{6}$$