Information Sciences 366 (2016) 12–30

Contents lists available at ScienceDirect

Information Sciences

journal homepage: www.elsevier.com/locate/ins

Simultaneous fault diagnosis for robot manipulators with actuator and sensor faults[☆]

Hong-Jun Ma[a,b,*], Guang-Hong Yang[a,b]

[a] College of Information Science and Engineering, Northeastern University, Shenyang, People's Republic of China
[b] State Key Laboratory of Synthetical Automation for Process Industries, Northeastern University, Shenyang, People's Republic of China

ARTICLE INFO

Article history:
Received 28 November 2014
Revised 27 February 2016
Accepted 15 May 2016
Available online 24 May 2016

Keywords:
Fault diagnosis
Fault location
Adaptive observer
Manipulator
Robots

ABSTRACT

This paper studies a model-based fault detection and isolation (FDI) scheme for robot manipulators with actuator and sensor faults. Without adding redundant joint sensor measurements, the multiple faults simultaneously occurring in the actuators and sensors of the manipulator are detected, estimated and isolated. Considering *Lipschitz*-like nonlinearities and modeling uncertainties, a nonlinear adaptive observer is presented to estimate the faulty parameters with a pre-specified estimation error bound. The performances of the proposed FD scheme, including the robustness of observers to the uncertainties, the accuracy of fault estimation and the rapidity of fault diagnosis, are rigorously analyzed. The proposed approach is verified by a simulation of Integrated Motion Inc. (IMI) two-link, revolute, direct-drive robot manipulator.

1. Introduction

In recent years, robot reliability and its fault tolerance have received significant attentions, especially in robotic applications in remote and hazardous environments (e.g., the medicinal or biotechnological treatment of disease requiring patient-robot interfacing). For robot operation in the presence of a fault, the following factors are usually taken into considerations: detection of the fault; characterization, quantification, and identification of the fault; and then response to the fault by halting the system and/or accommodating for the fault [34]. The research on fault detection and isolation has becoming especially important for its various implications (e.g., avoiding major plant breakdowns and catastrophes; safety problems; fast and appropriate responses to emergency situations). In general, diagnosing a fault during a small time interval is a fundamental requirement to reducing the probability of hardware damages or critical injuries to the people around the controlled system [1,14,16,18,21,23,28,39,40,49,62,63].

The purpose of fault diagnosis is to detect and isolate the faults, i.e., to decide, among a set of possible faults, which ones are actually present. At the same time, the faults are usually estimated in magnitude and direction for exactly locating. To this end, model-based methods [13] for fault diagnosis rely on the design of residuals, that is, the signals computed from sensor measurements and the applied system inputs with the aid of a mathematical description of the monitored

☆ This work was supported in part by the Funds of National Science of China (Grant nos. 61273148, 61273155, 61420106016, 61473067, 61473068), the Research Fund of State Key Laboratory of Synthetical Automation for Process Industries (Grant no. 2013ZCX01), and the Fundamental Research Funds for the Central Universities (No. N110804001, N130504005, N140402002).

* Corresponding author at: College of Information Science and Engineering, Northeastern University, Shenyang, People's Republic of China. Tel.: +86 024-83681939.

E-mail addresses: mahongjun@ise.neu.edu.cn (H.-J. Ma), yangguanghong@ise.neu.edu.cn (G.-H. Yang).

http://dx.doi.org/10.1016/j.ins.2016.05.016

system. Typically, each of the residuals is sensitive to a subset of the possible faults, such that fault diagnosis is achieved by evaluating these residuals. Among the model-based fault detection (FD) approaches, the most widely adopted method is the observer-based method [22], based on applying diagnosis observers to estimate a set of relevant variables characterizing the system.

Early observer-based fault diagnosis approaches to FD for robotic systems were presented by including an observer for the whole state of the plant [2,32,50,51], and model parameter estimation [24,25]. After that, these ideas were extended by estimating a specific part of the system state and obtaining a residual [20,33]. To improve the robustness of the observers to noise and uncertainties, several fault diagnosis techniques were developed, such as the generalized momenta-based approaches [11], the Kalman filters-based method [35], the learning methodologies [44], as well as the prediction-error-based approach [15], to name just a few. To achieve an exact convergence of the observer state in the uncertain practical environments, the sliding mode-based techniques were exploited to perform fault estimation [3,8]. Then, for its practicability and robust feature, the slide mode-based techniques were combined in several effective ways [6,7,9,42,43]. To improve the ability to estimate and isolate of the faults, the adaptive observer-based residual generation methods have been developed for linear time-varying systems, stochastic systems and nonlinear systems [37,45–48,52]. It is worth noting that in most of the works dealing with nonlinearities perturbed by unknown parameters of fault, the adaptive control problem is rather considered and the parameter convergence is rarely addressed. At the same time, the recent further developments in adaptive observer techniques (e.g. [10,19,26,29–31,38,41,53–61]) have shed light on fault diagnosis in nonlinear dynamic systems including robot manipulators.

The above-mentioned approaches are mainly focused on either faults affecting the sensor or the actuator and assume that a single fault acts only on one component of the system at a time. To the best of our knowledge, for robot manipulators, only a few FDI schemes are capable of detecting and isolating both sensor and actuator failures (e.g., [4–7,36]). The FDI scheme proposed in [7] is able to detect nonsimultaneous sensor and actuator faults and, if one knows that faults occurred only on actuators, then it is possible to isolate multiple simultaneous faults on actuators. The results in [4,5] cannot deal with, however, physical interaction of the manipulators with the external environment. To achieve simultaneous diagnosis, it is assumed in [6,36], that each manipulator is equipped with redundant sensors, i.e., a couple of identical sensors (proprioceptive sensors, wrist-mounted force/torque sensor or vision sensors etc.) to provide both joint position and joint velocity readings.

In this paper, an FDI scheme of monitoring multiple faults in the actuators and sensors of robot manipulators is presented without adding redundant sensors. An adaptive observer technique is developed to detect and estimate the multiple actuator faults and sensor faults, even when the actuator faults and sensor faults simultaneously occur. Considering unstructured modeling uncertainties, a bounded disturbance term is introduced in the observer design. Technically, an adaptive observer is constructed under some special regularity assumptions and a persistence excitation condition. The proposed observer error system contains the errors in estimating the actuator and sensor faults and two auxiliary variables. Then the convergences of the estimates of the multiple faults and the auxiliary variables are achieved if the filtered signals of the fault direction vectors $\Psi_u(t)$ (for actuator) and $\Psi_y(t)$ (for sensor) satisfy a persistent excitation condition. By achieving the exponential convergence in the estimate errors of the simultaneous multiple faults in actuators and sensors and the auxiliary variables, the behaviors of the residual signals are rigorously analyzed. Then a group of residual signals and thus the proposed fault diagnosis scheme are construed to perform the simultaneous fault detection and isolation. The fault diagnosis scheme proposed in this paper proves to detect simultaneous sensor and actuator faults and, also provides good isolation and identification capabilities independent from the specific adopted second-order sliding mode (SOSM) law and the number of sensors.

1.1. Notations

$\mathbb{R}^{m\times n}$ is the set of $m \times n$ real matrices. $\mathbb{N}$ is the set of natural numbers. The superscript T means transpose for real matrices. I_n is the identity matrix of dimension n. All matrices, if not explicitly stated, are supposed to have compatible dimensions. $diag\{D_1, \ldots, D_n\}$ is a block-diagonal matrix with matrices D_i, $i = 1, \ldots, n$, on its diagonal. A matrix is Hurwitz (or stable) if all of its eigenvalues have strictly negative real part. The matrix inequality $F \le G$ means that F and G are symmetry matrices and that $F - G$ is semi-negative definite. For matrix $F \in \mathbb{R}^{n\times n}$, $\lambda_{max}(F)$ and $\lambda_{min}(F)$ are its maximum eigenvalue and the minimum eigenvalue respectively. $F\otimes G$ denotes the Kronecker product of two matrices $F \in \mathbb{R}^{m\times n}$ and $G \in \mathbb{R}^{p\times q}$. $0_{m\times n} \in \mathbb{R}^{m\times n}$ is the matrix with all entries be zero and $1_{m\times n} \in \mathbb{R}^{m\times n}$ represents the matrix with all entries be one. Let E_j denote the jth column of the identity matrix I_n.

The paper is organized as follows. In Section 2, the considered system model is given. In Section 3, the proposed approach to fault detection and isolation through adaptive estimation is presented. A numerical example is presented in Section 4 before the paper is concluded in Section 5.

2. Robot manipulator model

2.1. Lagrangian representation

According to the Lagrangian approach [27], the mechanical and electrical dynamics of a fault-free n-joint robot manipulator (see Fig. 1) is described below

$$\tau = \mathbf{B}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{n}(\mathbf{q}, \dot{\mathbf{q}}), \mathbf{n}(\mathbf{q}, \dot{\mathbf{q}}) = \mathbf{C}(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}} + \mathbf{G}(\mathbf{q}) + \mathbf{F}_v\dot{\mathbf{q}} \tag{1}$$