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A hierarchical multiple-model approach for detection and isolation of robotic actuator faults

Tesheng Hsiao *, Mao-Chiao Weng

Department of Electrical Engineering, National Chiao Tung University, 1001 Ta Hsueh Rd., Hsinchu, Taiwan

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ABSTRACT

Modern robotic systems perform elaborate tasks in complicated environments and have close interactions with humans. Therefore fault detection and isolation (FDI) schemes must be carefully designed and implemented on robotic systems in order to guarantee safe and reliable operations. In this paper, we propose a hierarchical multiple-model FDI (HMM-FDI) scheme to detect and isolate actuator faults of robot manipulators. The proposed algorithm performs FDI in stages and refines the associated *model set* at each stage. Consequently only a small number of models are required to detect and isolate various types of *unexpected* actuator faults, including abrupt faults, incipient faults, and simultaneous faults. In addition, the computational load is alleviated due to the reduced-sized model set. The relation between the fault detection stage of the HMM-FDI scheme and the likelihood ratio test is explicitly revealed and theoretical upper bounds of the false alarm and missed detection probabilities are evaluated. Then we conduct experiments to demonstrate the ability of the HMM-FDI scheme in successful and immediate detection and isolation of actuator faults.

1. Introduction

Robotic systems are widely used to carry out various missions that require high precision, reliability and safety. Typical robotic applications are, to name but a few, industrial manufacturing, demining, hazardous waste cleanup, and outer space exploration. In addition, recent advances in intelligent robots have inspired a large number of emerging applications such as housekeeping, medical surgeries, and the elderly home care. In order to accomplish these increasingly elaborate tasks, modern robots turn into ever complicating systems. However, the more complex the robotic systems are, the more likely they are to break down. Unfortunately, the unexpected breakdown may either incur a cost that is too high to be affordable (e.g. interruption of a space mission), or even worse, cause damage to users and their property due to close interactions with humans and environments. Therefore, faults of robotic systems must be taken care of properly in order to guarantee their safe operation. Procedures for dealing with faults include (i) detecting the occurrences of faults (fault detection), (ii) indicating faulty components (fault isolation), (iii) identifying features of faults (fault identification), and (iv) accommodating faults by dedicated control algorithms (fault tolerant control).

Fault detection and isolation (FDI) schemes have been investigated over the past three decades [1–3], and have been successfully applied to various safety-critical systems such as nuclear plants [4], flight control systems [5], vehicular drive-by-wire systems [6], automated highway systems [7,8], and robotic systems [9,10]. Commonly used techniques include state and parameter estimation [11–17], parity equations [18,19], neural networks [20,21], and multiple-model (MM) approaches [22–26]. On the other hand, fault tolerant control (FTC) can be realized with or without explicit FDI schemes [7,27–29]. In particular, applying FTC to robotic systems has drawn a lot of attention in the past [30–32].

In the aforementioned studies, faults are represented as either additive signals or multiple models. The former usually results in a complicated fault signal which is a function of the system state. Hence the fault signal cannot be treated as external disturbances, making it challenging to analyze and synthesize the FDI schemes. On the other hand, the latter represents each fault by a specific model that might be simple and structurally different from one another. Thus the multiple-model fault representation is more flexible and powerful, leading to the recent development of multiple-model FDI (MM–FDI) schemes.

For example, eight fault models were established for the air-intake system of a turbo-charged engine [22]; then structured hypothesis tests were used to detect the occurrences of faults. The multiple-model adaptive estimation (MMAE) algorithm, which runs parallel state estimators and calculates the probability of each model by Bayes' rule, has been applied to the flight control

* Corresponding author. Tel.: +886 3 5131249; fax: +886 3 5715998.
E-mail addresses: tshsiao@cn.nctu.edu.tw (T. Hsiao), mcw615@ymail.com (M.-C. Weng).

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system [33]. To improve the performance of multiple-model FDI (MM–FDI) schemes, the interacting multiple-model (IMM) algorithm was investigated [23] and applied to the satellite's attitude control system [24] as well as the aircraft lateral motion control system [25].

The aforementioned MM–FDI schemes enumerate all detectable and isolatable faults in the *model sets*. If an *unexpected* fault, i.e. a fault without a corresponding model in the model set, has occurred, the results of the MM–FDI schemes become unpredictable. Therefore, a large model set is required in order to detect and isolate as many faults as possible. Unfortunately, it is difficult, if not impossible, to design an exhaustive model set that contains every possible fault. Take the partial actuator fault [26] for example. The associated fault model incorporates a fixed multiplicative "effective factor" in the actuator's output, representing the reduction of the actuator's gain. Since the effective factor can be any number between 0 and 1, it is impossible to include all partial fault models in the model set. In fact, we are restricted to work on a finite model set, and we will show in Section 3 that expanding the model set results in a considerable increase of the computational load. Even though the computational load is affordable, a large model set is not recommended because some models may become indistinguishable from the input–output point of view, and then the MM–FDI schemes are unable to select the fittest model from the model set with "sufficient confidence". In short, MM–FDI schemes face a dilemma of avoiding unexpected faults by using a fine-grained model set while maintaining a tractable algorithm by limiting the size of the model set.

To tackle the model set design problem, Ru and Li [26] proposed the IM^{3}L algorithm that uses the IMM algorithm for estimating system state and the expectation-maximization (EM) algorithm for updating model parameters. Therefore the fault models are self-adaptive, relieving the need for a large model set. However only (multiple) abrupt total and partial faults were considered in [26].

In this paper, we propose a hierarchical multiple-model FDI (HMM-FDI) scheme as a solution to the model set design problem and apply it to detect and isolate actuator faults of robot manipulators. The ultimate goal of the proposed FDI scheme is to find out faulty joints in an early stage such that fault tolerant strategies can be launched in time to guarantee safe operation of the robotic system. In other words, any faulty joints must be indicated *before* the robotic system significantly deviates from its nominal performance, *no matter what kinds of faults have taken place*. To achieve this goal, the proposed HMM-FDI scheme works in stages. At each stage, the model set is refined such that only a small number of models are required. Therefore the HMM-FDI scheme avoids the need for enumerating all possible faults in the model set, while is endowed with the ability to detect and isolate various types of *unexpected* actuator faults, including abrupt faults, incipient faults, and simultaneous faults in a computationally efficient way. The relation between the fault detection stage of the HMM-FDI scheme and the likelihood ratio test is explicitly revealed and theoretical upper bounds of the false alarm and missed detection probabilities are evaluated. Then experiments are conducted to verify the performance and efficiency of the HMM-FDI scheme.

The remainder of this paper is organized as follows: Section 2 introduces the dynamic and kinematic models of the robot manipulator. Section 3 illustrates the notions of the MM–FDI methods and the related techniques. The HMM-FDI scheme is proposed in Section 4 while experimental results are presented in Section 5. Section 6 concludes this paper.

2. Dynamic and kinematic models of the manipulator

The dynamic equation of an n-joint manipulator is given as follows [34]:

$$\mathbf{M}(\mathbf{q}(t))\ddot{\mathbf{q}}(t) + \mathbf{C}(\mathbf{q}(t), \dot{\mathbf{q}}(t))\dot{\mathbf{q}}(t) + \mathbf{G}(\mathbf{q}(t)) + \mathbf{F}(\dot{\mathbf{q}}(t)) = \boldsymbol{\tau}(t) \quad (1)$$

where $\mathbf{q}(t), \dot{\mathbf{q}}(t), \ddot{\mathbf{q}}(t) \in \mathbb{R}^n$ are vectors of joint positions, velocities, and accelerations at time t, respectively. $\mathbf{M}(\mathbf{q}(t)), \mathbf{C}(\mathbf{q}(t), \dot{\mathbf{q}}(t)) \in \mathbb{R}^{n\times n}$ are the inertia matrix, and Coriolis and centrifugal matrix respectively. $\mathbf{G}(\mathbf{q}(t)), \mathbf{F}(\dot{\mathbf{q}}(t)), \boldsymbol{\tau}(t) \in \mathbb{R}^n$ denote the gravitational torque vector, friction vector, and control torque vector, respectively. For clarity, we will drop the notational dependence of all variables on t as long as it leads to no confusion.

Define the state vector of the manipulator as $\mathbf{x} = [\mathbf{q}^T, \dot{\mathbf{q}}^T]^T$. Because the proposed HMM-FDI scheme will be derived in the discrete-time domain, we apply the Euler's method to convert (1) to its discrete-time counterpart and obtain the following state space representation:

$$\mathbf{x}_{k+1} = \mathbf{x}_k + h\begin{bmatrix}\dot{\mathbf{q}}_k \\ \mathbf{f}(\mathbf{x}_k, \boldsymbol{\tau}_k)\end{bmatrix} + \begin{bmatrix}\mathbf{w}_k^p \\ \mathbf{w}_k^v\end{bmatrix} \quad (2)$$

where $\mathbf{f}(\mathbf{x}_k, \boldsymbol{\tau}_k) = \mathbf{M}^{-1}(\mathbf{q}_k)\left[\boldsymbol{\tau}_k - \mathbf{C}(\mathbf{q}_k, \dot{\mathbf{q}}_k)\dot{\mathbf{q}}_k - \mathbf{G}(\mathbf{q}_k) - \mathbf{F}(\dot{\mathbf{q}}_k)\right]$, h is the sampling time, and the subscript k denotes the kth sample. $\mathbf{w}_k = [(\mathbf{w}_k^p)^T, (\mathbf{w}_k^v)^T]^T$ is the process noise representing the model uncertainties and the approximation error due to the Euler's method.

We assume that only the joint positions are measurable. Thus the output equation of the manipulator is:

$$\mathbf{y}_k = \mathbf{C}\mathbf{x}_k + \mathbf{v}_k \quad (3)$$

where $\mathbf{C} = [\mathbf{I}_{n\times n}\mathbf{0}_{n\times n}]$ and $\mathbf{v}_k$ is the measurement noise which is assumed to be Gaussian distributed white noise with zero mean and covariance matrix $\mathbf{R}$.

In the context of the HMM-FDI scheme, the *dynamic model* consists of (2) and (3) along with the assumption that $\mathbf{w}_k$ is Gaussian distributed noise with zero mean and covariance matrix $\mathbf{Q}_k^D$. In addition, we assume that components of $\mathbf{w}_k$ are mutually uncorrelated, i.e. $\mathbf{Q}_k^D$ is a diagonal matrix. Note that we allow the covariance matrix to be time-varying.

Remark 1. It should be noted that the actual distribution of $\mathbf{w}_k$ may not be Gaussian; nevertheless the dynamic model *assumes* that $\mathbf{w}_k$ is Gaussian distributed and mutually uncorrelated, and treats the covariance matrix $\mathbf{Q}_k^D$ as a *tunable parameter of the model*, not a *physical quantity of the robot*. By tuning $\mathbf{Q}_k^D$ we change the "accuracy" of the dynamic model. If $\mathbf{Q}_k^D$ is set to an inappropriate value, then the dynamic model behaves poorly in predicting the motion of the manipulator; however, it is our intention to reduce the "relative accuracy" of one model w.r.t. the others for the purpose of fault detection and isolation. See Section 4 for more details.

On the other hand, we can predict the motion of the manipulator through the *kinematic relations* of joints. By kinematic relation we mean that the joint velocity is the first derivative of the joint position. Approximating the kinematic relation by the Euler's method yields

$$\mathbf{q}_{k+1} = \mathbf{q}_k + h\dot{\mathbf{q}}_k + \boldsymbol{\xi}_k^p \quad (4)$$

where $\boldsymbol{\xi}_k^p$ is the approximation error due to the Euler's method. On the other hand, if the differentiation relation is approximated by the backward difference equation, then we have

$$\dot{\mathbf{q}}_{k+1} = \frac{\mathbf{q}_{k+1} - \mathbf{q}_k}{h} + \boldsymbol{\xi}_k^v = \frac{(\mathbf{q}_k + h\dot{\mathbf{q}}_k + \boldsymbol{\xi}_k^p) - \mathbf{q}_k}{h} + \boldsymbol{\xi}_k^v \quad (5)$$

where $\boldsymbol{\xi}_k^v$ is the approximation error due to the backward difference equation. Combining (4) and (5) yields the following equation:

$$\mathbf{x}_{k+1} = \mathbf{A}^K\mathbf{x}_k + \mathbf{G}^K\boldsymbol{\xi}_k \quad (6)$$