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Fault Diagnosis for Manipulator Robot using Observers-Based Approaches

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Abstract. The objective of this work deals with the analysis and design of a fault detection and isolation technique (FDI) for a class of affine nonlinear systems using high gain observers. The observer is applied for robot manipulator named Articulated Nimble Adaptable Trunk "ANAT" in order to detect and isolate sensor fault. The simulation results prove the effectiveness, performances and the robustness of the approach.

Keywords: Fault detection, Robot manipulator, High gain observer, Residuals, Nonlinear systems.

1 Introduction

Recently, robot manipulators are the most important components of manufacturing and control processes. They have the impact: Improving productivity, increasing the quality of manufactured products, and reducing the cost of labor. Associated with the increasing industrial demands on safety, reliability, dependability and assuring the normal operation of this robot manipulator, the issue of FDI is important. Fault Detection and Isolation (FDI) techniques in robot manipulator is becoming one of the most phenomena in robotics in order to ensure higher levels of safety and productivity. Research, has been produced a considerable effort in seeking systematic approaches to fault detection for both linear and nonlinear dynamical systems. Several FD techniques for robot manipulators have been proposed in the literature, although the problem of their application to industrial robots has not been extensively investigated. The methods of fault detection can be separated into methods which don't use plant models and model-based approaches. For the first category are classical limit and trend value checks as well as signal analysis methods, for example, autocorrelation techniques, spectral analysis, etc. Normally, those methods need dedicated sensor systems. Observer-based, parameter estimation and parity relations techniques, on the other hand, the second class of fault detection schemes are the most relevant approaches. Therefore, different methods have been developed for detecting and isolating actuator and sensor faults on robot manipulators, such as parameter estimation, parity relations and observer-based approaches [1],[2],[3],[4]. One of the most popular of the model-based approaches to FDI is the observers-based techniques. The basic idea of observers-based methods consists reconstruct some or all system outputs from accessible process variables.

The fault indicators are generated by forming the differences between the estimated outputs and the actual outputs. However, special attention has to be paid when applying observer theory for fault detection and isolation. Observer-based method requires a model of the investigated process also. The model is operated parallel to the real process, the inputs to the model are the same as those to the real process. In contrast to classical state-space observers, e.g., Kalman filter, the diagnostic observers are output observers which are operated in an open-loop configuration. Assuming an exact model of the plant, the difference of measured and calculated process outputs (which is called a residual) will produce a nonzero value when a fault has occurred. A thorough overview of robust observer-based fault detection methods can be found in [5] and [6]. The main advantage of observer-based methods over parameter estimation methods is given by the fact that no special excitation is required. The observer-based method will work in steady state operation conditions as well.

The paper is organized as follows. High-gain observers used for the design of residual generators are development in section 2. Section 3 provides application for robot manipulator. The conclusion is given in section 4.

2 High Gain Observer

In general, an observer is a dynamic system that provides estimations of the current state of the system, by using the previous knowledge of the inputs and outputs of the system [11].

Consider the following class of affine MIMO nonlinear system with m inputs and p outputs defined by the following state representation [15]:

$$\begin{cases} \dot{x} = f(x, d, t) + \sum_{i=1}^m g(x, t)u(t) \\ y = Cx \end{cases} \quad (1)$$

where $x \in \mathbb{R}^n$ is the state variable vector, $u(t) \in \mathbb{R}^m$ is the input control vector and $y \in \mathbb{R}^p$ is the output vector, $f(x, d, t)$ is the n -dimensional unknown nonlinear dynamics and d is the disturbance, $g(x, t)$ is the $(n \times m)$ nonlinear control dynamics matrix, C is the $(p \times n)$ output distribution matrix.

The system (1) has the input $u(t) \in \mathbb{R}^m$ in which has a set of admissible values of the input. It is also assumed that there exists a physical domain $\Omega \in \mathbb{R}^n$ (open, bounded) of evolution of the input and that is the domain of interest of the system.

Suppose that system (1) it is observable in the sense of rank and that $u = 0$ an input universal, then the jacobian $\{h_1, L_f h_1, \dots, L_f^{n-1} h_1, h_2, L_f^{n-1} h_2, L_f^{n-1} h_p\}$ with respect to $x \in \mathbb{R}^n$ and x is of rank n . In the vicinity of a regular point one can select a subset of full rank:

$$\phi = \{z_1, \dots, z_n\} \{h_1, L_f h_1, \dots, L_f^{n-1} h_1, h_2, L_f^{n-1} h_2, L_f^{n-1} h_p\} \quad (2)$$

with $\sum_{k=1}^p \eta_k = n$

The input $h_k(x)$ intervenes in the order η_k . This determines a local coordinate

system in which the system (1) is written as:

$$\begin{cases} \dot{z} = Az + \tilde{\varphi}(z) + \bar{\varphi}(z)u \\ y = Cz \end{cases} \quad (3)$$

with $z \in \mathbb{R}^n, u \in \mathbb{R}^m, y \in \mathbb{R}^p$

$$A = \begin{bmatrix} A_1 & & \\ & \ddots & \\ & & A_p \end{bmatrix}; B = \begin{bmatrix} C_1 & & \\ & \ddots & \\ & & C_p \end{bmatrix}; \tilde{\varphi}(z) = \begin{bmatrix} \tilde{\varphi}_1(z) \\ \vdots \\ \tilde{\varphi}_p(z) \end{bmatrix}; \bar{\varphi}(z) = \begin{bmatrix} \bar{\varphi}_1(z) \\ \vdots \\ \bar{\varphi}_p(z) \end{bmatrix} \quad (4)$$

with

$$A_k = \begin{bmatrix} 0 & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 1 \\ 0 & 0 & \dots & 0 \end{bmatrix}; \tilde{\varphi}_k(z) = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ \tilde{\varphi}_k(z) \end{bmatrix}; \bar{\varphi}_k(z) = \begin{bmatrix} \bar{\varphi}_k(z) \\ \vdots \\ \bar{\varphi}_{\eta_k k}(z) \end{bmatrix}; C_k = [1 \ 0 \ \dots \ 0] \quad (5)$$

with $\tilde{\varphi}_k(z) = L_f^{\eta_k} h_k$, $\bar{\varphi}_k(z) = L_g L_f^{i-1} h_k$; $\dim(A_k) = (\eta_k \times \eta_k)$,

$\dim(C_k) = (1 \times \eta_k)$

and $\dim(\tilde{\varphi}_k(z)) = \dim(\bar{\varphi}_k(z)) = (\eta_k \times 1)$ for $k = 1, \dots, p; i = 1, \dots, \eta_k$.

For the following theorem, is not used the linearity in u , the following system is then considered:

$$\begin{cases} \dot{z} = Az + \varphi(z, u) \\ y = Cz \end{cases} \quad (6)$$

Let K be a matrix $(n \times p, p)$ such that

$$K = \begin{bmatrix} K_1 & & \\ & \ddots & \\ & & K_p \end{bmatrix} \quad (7)$$

(with K_k of dimension $n \times 1$), such that for each block k , the matrix $A_k - K_k C$ have negative real parts. Then the system is uniformly locally observable, and it exists $T_0 > 0$, such that, for every T , such $0 < T < T_0$, the following system Constitutes an observer for the system (6):

$$\dot{\hat{z}} = A\hat{z} + \varphi(\hat{z}, u) + \Lambda^{-1}(T, \delta)K(y - C\hat{z}) \quad (8)$$

with $\hat{z}_{\mu} k = y_k$

$\hat{z}_j = \hat{z}_j \neq \mu_k$,

$$A(T, \delta) = \begin{bmatrix} T^{\delta_1} \Delta_1(T^{\delta_1}) & & \\ & \ddots & \\ & & T^{\delta_p} \Delta_p(T^{\delta_p}) \end{bmatrix} \text{ with } \Delta_k(T) = \begin{bmatrix} T^{\delta_k} & & \\ & \ddots & \\ & & T^{2\delta_k} \\ & & & \ddots \\ & & & & T^{\eta_k \delta_k} \end{bmatrix} \quad (9)$$

Moreover, the standard of the observation error is bounded by an exponential whose decay rate can be chosen arbitrarily large.

Remark1. The system

$$\left\{ \begin{aligned} \dot{\hat{z}} &= A\hat{z} + \varphi(\hat{z}, u) + \Lambda^{-1}(T, \delta)K(y - C\hat{z}) \end{aligned} \right. \quad (10)$$

Also an observer for system (6). If a change of variable $z = \phi(x)$ has been necessary, it is necessary to return to the old database by $(\hat{x}) = \phi^{-1}(\hat{z})$. By applying this change of coordinates to the previous system, we obtain the observer in the old coordinates:

$$\left\{ \begin{aligned} \dot{\hat{x}}(t) &= f(\hat{x}(t)) + \sum_{i=1}^m g_i(\hat{x}(t))u_i(t) + \left[\frac{\partial\phi(x)}{\partial x}\right]_{\hat{x}}^{-1}\Lambda^{-1}K[y(t) - C\hat{x}(t)] \end{aligned} \right. \quad (11)$$

Remark2. The observer is written in the new coordinates as a system copy plus a non-linear correction. Implementation requires writing the observer into the original frame. Therefore the system becomes:

$$\left\{ \begin{aligned} \dot{\hat{x}}(t) &= f(\hat{x}(t)) + \sum_{i=1}^m g_i(\hat{x}(t))u_i(t) + \left[\frac{\partial\phi(x)}{\partial x}\right]_{\hat{x}}^{-1}\Lambda^{-1}K[y(t) - C\hat{x}(t)] \\ y &= Cx \end{aligned} \right. \quad (12)$$

The term of correction $\left[\frac{\partial\phi(x)}{\partial x}\right]_{\hat{x}}^{-1}\Lambda^{-1}K[y(t) - C\hat{x}(t)]$ then explicates as follows:

$$\left[\frac{\partial\phi(x)}{\partial x}\right]_{\hat{x}^{-1}} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}; \Lambda^{-1} = \begin{bmatrix} T^{-\delta_1} & 0 & 0 & 0 & 0 \\ 0 & T^{-2\delta_1} & 0 & 0 & 0 \\ 0 & 0 & T^{-\delta_2} & 0 & 0 \\ 0 & 0 & 0 & T^{-2\delta_2} & 0 \\ 0 & 0 & 0 & 0 & T^{-\delta_3} \end{bmatrix} \quad (13)$$

The gain T^{-1} must be selected as $0 < T \leq T_0 < 1$. T_0 is defined according to different parameters (η^2 , the constant Lipschitz of the function $\varphi(z, u)$ defined by variable change,...). And the gain K is given by :

$$K = \begin{bmatrix} K_1 & & & & \\ & \ddots & & & \\ & & & & \\ & & & & K_5 \end{bmatrix} \quad (14)$$

The pair (A,C) is observable, and it is an easy matter to assign eigenvalues to the matrix $A-KC$, that has the companion structure :

$$A - KC = \begin{bmatrix} -K_1 & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ -K_{n-1} & 0 & \dots & 1 \\ -K_n & 0 & \dots & 0 \end{bmatrix} \quad (15)$$

If a n -pla $\lambda = (\lambda_1, \dots, \lambda_n)$ of eigenvalues has to be assigned, the vector $K(\lambda)$ is the vector that contains the coefficients of the monic polynomial that has λ as

roots. If the assigned eigenvalues are distinct, matrix $A-KC$ can be diagonalized by a Vandermonde matrix :

$$V \equiv V(\lambda) \begin{bmatrix} \lambda_1^{n-1} & \dots & \lambda_1 & 1 \\ \vdots & \ddots & \vdots & \vdots \\ -k_{n-1} & \dots & \lambda_n & 1 \end{bmatrix} \quad (16)$$

So that

$$V(\lambda)(A - K(\lambda)C)V(\lambda)^{-1} = \text{diag}\{\lambda\} = \Lambda \quad (17)$$

Remark3: Given a set λ of n eigenvalues to be assigned to $A-KC$, the gain $K(\lambda)$ is readily computed through the formula :

$$K(\lambda) = -V^{-1}(\lambda)[\lambda_1^n \dots \lambda_n^n]^T \quad (18)$$

So, the term of correction of the system is:

$$\left[\frac{\partial \phi(x)}{\partial x} \right]_{\hat{x}}^{-1} \Lambda^{-1} K [y(t) - C\hat{x}(t)] = \begin{bmatrix} T^{-\delta_1} K_1 (q_1 - \hat{q}_1) \\ T^{-2\delta_1} K_2 (q_2 - \hat{q}_2) \\ T^{-\delta_2} K_3 (q_3 - \hat{q}_3) \\ T^{-2\delta_2} K_4 (q_4 - \hat{q}_4) \\ T^{-\delta_3} K_5 (q_5 - \hat{q}_5) \end{bmatrix} \quad (19)$$

3 Application : Robot manipulator

3.1 System Description and Modeling

To illustrate the effectiveness of the proposed approach, we consider Articulated Nimble Adaptable Trunk robot arm with 5 degree of freedom (DOF). The dynamic model is further specified by the well-known equation for rigid manipulators:

$$\ddot{q} = -M(q)^{-1}F(q, \dot{q}) + M(q)^{-1}\tau \quad (20)$$

where M is the inertia matrix, which is symmetric and positive definite. Thus, $M(q)^{-1}$ always exists. F is the centrifugal, coriolis, and gravity vector; q is the joint position vector; τ is the torque input vector of the manipulator. Let $x = [X_1^T, X_2^T]^T$ the state vector with $X_1 = [q_1, q_2, q_3, q_4, q_5]^T$ and $X_2 = [\dot{q}_1, \dot{q}_2, \dot{q}_3, \dot{q}_4, \dot{q}_5]^T$, and $y = X_1$ is the output vector. The description of the system can be given in state representation form as follows:

$$\begin{cases} \dot{x}_1 = x_6 \\ \dot{x}_2 = x_7 \\ \dot{x}_3 = x_8 \\ \dot{x}_4 = x_9 \\ \dot{x}_5 = x_{10} \\ \dot{x}_6 = f_1(x, d, t) + \sum_{i=1}^5 g_{1i}(x, t)u_i(t) \\ \dot{x}_7 = f_2(x, d, t) + \sum_{i=1}^5 g_{2i}(x, t)u_i(t) \\ \dot{x}_8 = f_3(x, d, t) + \sum_{i=1}^5 g_{3i}(x, t)u_i(t) \\ \dot{x}_9 = f_4(x, d, t) + \sum_{i=1}^5 g_{4i}(x, t)u_i(t) \\ \dot{x}_{10} = f_5(x, d, t) + \sum_{i=1}^5 g_{5i}(x, t)u_i(t) \end{cases} \quad (21)$$

where $g(x, t) = M(q)^{-1}$; $u_i = \tau_i$ for $i = 1 : 5$; $f(x, d, t) = -M(q)^{-1}F(q, \dot{q})$

3.2 High gain observer applied to robot manipulator

Using the system model (1), a high gain observer is developed as explained in section 2 in order to improve the effectiveness of the proposed method in which is written as :

$$\begin{cases} \dot{\hat{x}}(t) = f(\hat{x}(t)) + \sum_{i=1}^m g_i(\hat{x}(t))u_i(t) + \left[\frac{\partial \phi(x)}{\partial x}\right]_{\hat{x}}^{-1} \Lambda^{-1} K [y(t) - C\hat{x}(t)] \\ y = Cx \end{cases} \quad (22)$$

The gain K and T , show the effectiveness of this observer. Thus, the choice of the gain of high-gain observer is based on a compromise between the speed of convergence of the observer and insensitivity to measurement noise. The gain K are chosen according to Remark3, and T between 0 and 1.

3.3 Simulation results

The state estimation error $r(t)$ can be calculated as:

$$r(t) = y(t) - \hat{y}(t) \quad (23)$$

The residuals are supposed to differ from zero in case of faults $r(t) \neq 0$ and equal to zero when there are no faults on the sensors $r(t) = 0$.

So the the residuals are evaluated as:

$$r_1 = |q_1 - \hat{q}_1|; \quad r_2 = |q_2 - \hat{q}_2|; \quad r_3 = |q_3 - \hat{q}_3|; \quad r_4 = |q_4 - \hat{q}_4|; \quad r_5 = |q_5 - \hat{q}_5| \quad (24)$$

Table I represents the fault signatures matrix for these residuals. Assuming that simultaneous faults cannot occur, we find that the signatures for each of the failures are quite different.

Table 1. Fault signatures matrix

d_i/r_i	r_1	r_2	r_3	r_4	r_5
d_1	1	0	0	0	0
d_2	0	1	0	0	0
d_3	0	0	1	0	0
d_4	0	0	0	1	0
d_5	0	0	0	0	1

We simulate the system during $T = 10$ s for residuals evolution. It is also noted that all faulty signals are additive.

- a fault d_1 is injected on the first joint (q_1) at the time $t = 1$ s and amplitude '1'. Figure (1) shows that the residual r_1 is different from zero during the time of fault existence, and the residuals ($r_2; r_3; r_4; r_5$) are equal to zero.

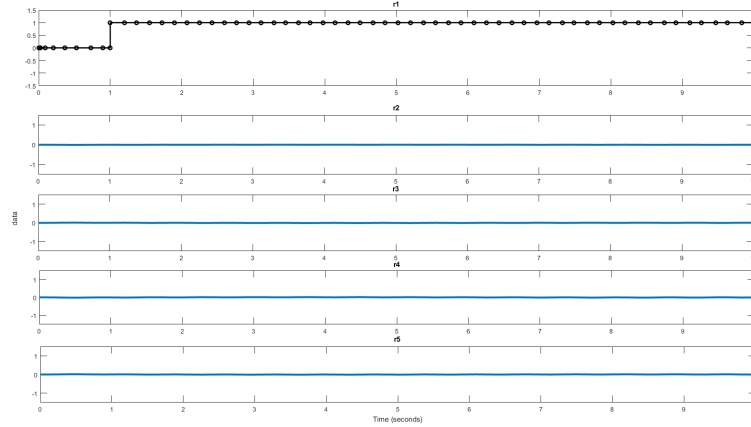
**Fig. 1.** Residuals evolution of the system with fault d_1

Figure (2), show residuals evolutions. The same procedure applied for the other articulations. In each figures we detected and isolated an articulation.

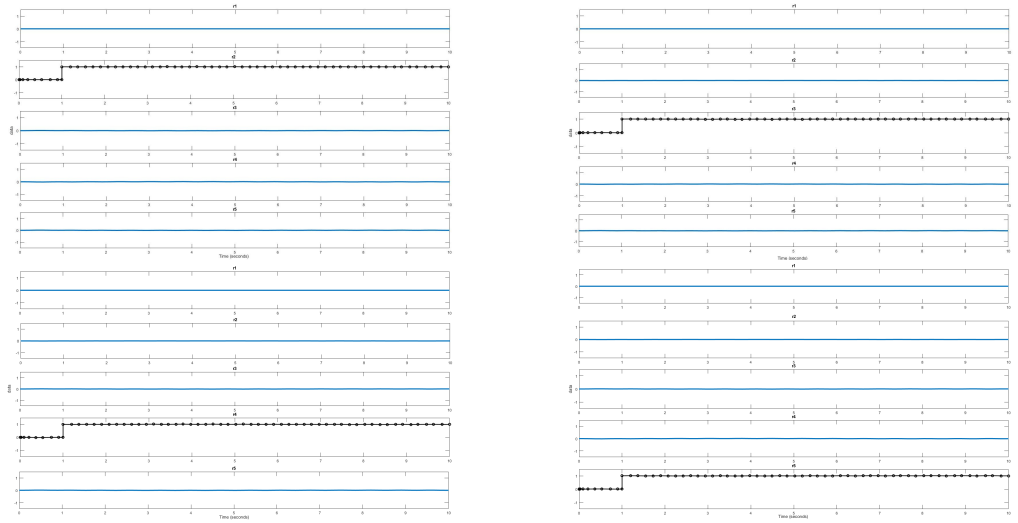


Fig. 2. Residuals evolution of the system with fault applied for articulations q_2, q_3, q_4, q_5

So, we can say that the proposed methods can give a good results and it can detect and isolate the sensor faults in a robot manipulator.

4 Conclusion

In Conclusion, a technique for fault detection and isolation based on high gain observer, for a class of affine nonlinear systems has been proposed. The approach is applied to a robot manipulator. Through the simulation results, it is shown that all faults defined in specifications are detected and isolated.

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