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Actuator fault detection and isolation for robot manipulator using higher order sliding mode observers

Khaoula Oulidi Omali, Mohammed Nabil Kabbaj, Mohammed Benbrahim
USMBA, LISTA
LISTA, Sidi Mohamed Ben Abdellah University Fez, Morocco

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ABSTRACT

Fault detection and isolation (FDI) method for actuator faults for robot manipulator by applying a model-based FDI fault, which may happen on a specific component of the system. To detect and isolate actuator faults, higher order sliding mode Unknown Input Observers (UIO) are proposed to make analytical redundancy. The observers input laws are designed according to the so-called Super-Twisting Second Order Sliding Mode Control (SOSMC) technique and they are proved to be able to guarantee the exponential convergence of the fault estimate to the actual fault signal. The simulation results show the effectiveness and robustness for the proposed approach.

Corresponding Author:

Khaoula Oulidi Omali,
USMBA, LISTA,
LISTA, Sidi Mohamed Ben Abdellah University Fez, Morocco.
Email: khaoula.oulidiomali@usmba.ac.ma

1. INTRODUCTION

A precise dynamic model of the system to be tested must be formulated to design a high performance controller. Its parameters should be equally precisely identified. Furthermore applies to industrial robots. in that event, the problem of identification becomes especially complex because of the presence of nonlinearities and coupling effects, typical of robotic systems, by dint of the inertial, friction torques, gravity, centripetal and friction torques [4].

The presence of a fault can be modeled as an unexpected change in system parameters or by the presence of unknown signals in the industry. In a robot manipulator, a fault be able to occur on a actuator, a sensor or a mechanical component of the system. specific Actuator and sensor faults are more common thanks to the presence of electrical devices, which possibly be subject for a lot of possible criticality.

Diagnostic devices generate on-line diagnostic signals in order to detect and isolate the presence of fault. Specific methods considered to surmount this disadvantage, as like the use of Kalman filters [6], or generalized moments, see [8]. These approaches, in the presence of typical uncertainties of applied applications, can not have the possibility exactly to converge from the state of the system to the state of the observer. To minimize this drawback, sliding mode techniques are also frequently adopted to perform status observation [10, 11] owing to their simplicity of design and robustness. Usually, the FDI can be treat by incorporating various sliding mode observers [12, 13].

The aim of this paper is to study the performance in terms of the robustness and diagnostic capabilities of sliding-mode input law for the observer. specifically , second-order sliding mode (SOSM) law, the super-twisting law [17] is considered. The diagnostic technique proposed in this work proves to be capable to detect non-simultaneous sensor and actuator faults, specially for actuator.

2. THE MANIPULATOR MODEL

The equations of motion of an n Degree of Fredeem (DOF) robot manipulators are described according to the Euler-Lagrange theory, as:

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

where $q, \dot{q}, \ddot{q} \in \mathbf{R}^n$ are the joint position, velocity and acceleration vectors, respectively, $M(q) \in \mathbf{R}^{(n\times n)}$ is the inertia matrix (symmetrical definite positive, thus, $M(q)^{-1}$ always exists), $C(q,\dot{q}) \in \mathbf{R}^{(n\times n)}$ is the centrifugal and Coriolis matrix, $G(q) \in \mathbf{R}^n$ is the gravitational vector, $F(\dot{q}) \in \mathbf{R}^n$ is the vector of viscous friction torque at the joints. Now, introducing the variables $x_1(t) = q(t)$, $x_2(t) = \dot{q}(t)$, model 1 can be rewritten in state space representation as:

$$\begin{cases} \dot{x}_1(t) = x_2(t) \\ \dot{x}_2(t) = f(\tau(t), x_1(t), x_2(t)) \\ h(t) = x_1(t) \end{cases} \tag{2}$$

Where the term $f(\tau(t), x_1(t), x_2(t))$ is obtained after simple algebric manipulation of (1), i.e.,

$$f(\tau(t), x_1(t), x_2(t)) = M^{-1}(x_1(t))(\tau(t) - n(x_1(t), x_2(t))) \tag{3}$$

As previously mentioned, when faults affect the actuators, the input torque for the mechanical system is different from $\tau(t)$. Then, in case of input faults, (1) becomes:

$$\tau(t) + \Delta\tau(t) = M(x_1(t))\dot{x}_2(t) + n(x_1(t), x_2(t)) \tag{4}$$

and, as a result, the state space representation is:

$$\begin{cases} \dot{x}_1(t) = x_2(t) \\ \dot{x}_2(t) = f(\tau(t) + \Delta\tau(t), x_1(t), x_2(t)) \\ q(t) = x_1(t) \end{cases} \tag{5}$$

where $f(\tau(t) + \Delta\tau(t), x_1(t), x_2(t))$ is analogous to (3). In practice, model (3) is not exactly known and must be identified. Then, in case of faults, the following relationship holds.

$$\begin{cases} f(\tau(t), x_1(t), x_2(t)) = M^{-1}(x_1(t))(\tau(t)+ \\ \Delta\tau(t) - \hat{n}(x_1(t), x_2(t)) - \eta(t)) \end{cases} \tag{6}$$

$$\eta(t) = n(x_1(t), x_2(t)) - \hat{n}(x_1(t), x_2(t)) \tag{7}$$

When $\eta(t)$ is uncertain and $\hat{n}(q,\dot{q})$ is the known part of the model. Yet, by virtue of the particular application considered, $\eta(t)$ can be assumed to be bounded. Obviously, to perform fault diagnosis, one has to rely only on the known part of model (3). Indeed, after a suitable identification procedure, such as the one proposed in [19], it is feasible (in absence of faults) to determine only an approximated representation of $f(.)$, i.e.

$$f(\tau(t), x_1(t), x_2(t)) = M^{-1}(x_1(t))(\tau(t) - \hat{n}((x_1(t), x_2(t)) \tag{8}$$

in order that the actually usable model is:

$$\begin{cases} \dot{x}_1(t) = x_2(t) \\ \dot{x}_2(t) = \hat{f}(\tau(t), x_1(t), x_2(t)) \\ q(t) = x_1(t) \end{cases} \tag{9}$$

3. THE PROPOSED DIAGNOSTIC SCHEME

By relying on the so-called Unknown Input Observer (UIO) approach [11], efficient estimators of the input torques can be designed [21]. In this work, the UIOs of sliding mode type is proposed in order to detect the actuator faults. The proposed UIOs can be jointly described as a multi-input-multi-state second order sliding mode observers.

3.1. Observer Design

Let us consider the observer:

$$\begin{cases} \hat{x}_1(t) = \hat{x}_2(t) + z_1(t) \\ \hat{x}_2(t) = \hat{f}(\tau(t), x_1(t), \hat{x}_2(t)) + z_2(t) \end{cases} \tag{10}$$

where $\hat{x}_1(t), \hat{x}_2(t) \in \mathbf{R}^{2n}$ are the observer states, and $z(t) = [z_1(t), z_2(t)]T$ is an auxiliary input signal, which is designed relying on the sliding mode approach, as will be clarified. This signal is introduced so as to permit and guarantee the convergence of the observer states to the actual state of the system. Each component of $z(t)$ is an input law of the observer.

3.2. Dynamics of the Observer Error

The proposed fault diagnostic scheme requires to steer to zero the signal $e(t) = [e_1(t), e_2(t)]^T \in \mathbf{R}^{2n}$, the components of which are given by:

$$\begin{cases} e_1(t) = x_1(t) - \hat{x}_1(t) \\ e_2(t) = x_2(t) - \hat{x}_2(t) \end{cases} \tag{11}$$

By steering to zero these quantities, it is possible to guarantee that the observer (10) gives a good estimation of the unknown input, as it will be shown in the following.
The dynamics of the error variable $e(t)$ is represented by a second order dynamical system:

$$\begin{cases} \dot{e}_1(t) = e_2(t) - z_1(t) \\ \dot{e}_2(t) = f(\tau(t), x_1(t), x_2(t)) - \hat{f}(\tau(t)+ \\ \Delta\tau(t), x_1(t), \hat{x}_2(t)) - z_2(t) \end{cases} \tag{12}$$

which can be rewritten as:

$$\begin{cases} \dot{e}_1(t) = e_2(t) - z_1(t) \\ \dot{e}_2(t) = M^{-1}(x_1(t)) - (\Delta\tau(t) - \eta(t)) - z_2(t) \end{cases} \tag{13}$$

Now, Second Order Sliding Mode approach is studied to design the multi-input-multi-state UIO input law. This approach is the so-called Super-Twisting [17]. The proposal will be depicted in the next subsections.

3.3. Super-Twisting based Observer

The design of the observer input laws which are the components of $z(t) = [z_1(t), z_2(t)]^T$ using a Super-Twisting based approach (see [17]) is given by:

$$\begin{cases} z_1(t) = \lambda\sqrt{|s\prime|}sign(s\prime(t)) \\ z_2(t) = \alpha sing(s\prime(t)) \end{cases} \tag{14}$$

Where $s\prime(t) = e_1(t) = x_1(t) - \hat{x}_1(t)$. It can be proved that a suitable choice of λ and α exists such that, starting from any initial condition $[e_1(0), e_2(0)]^T$, the condition:

$$\begin{cases} e_1(t) = 0 \\ e_2(t) = 0 \end{cases} \tag{15}$$

is guaranteed in finite time (the proof of this claim can be developed as in [14]). To implement the proposed method, the terms α and λ have been chosen after an experimental tuning procedure. Note that the term $z_2(t)$ is a discontinuous signal and, by virtue of the filtering action considered in [22], the second equation of the system (13) can be rewritten as:

$$z_{2eq}(t) = M^{-1}(x_2(t))(\Delta\tau(t) - \eta(t)) \tag{16}$$

where $z_{2eq}(t)$ is the equivalent input signal corresponding to the discontinuous signal $z_2(t)$. Thus, theoretically, the equivalent input signal is the result of an infinite switching frequency of the discontinuous term

$\alpha sing(s\prime(t))$. In fact, the implementation of the observer produces high switching frequency (since, in practice, one can only implement $z_2(t)$ as in (14) and not $z_{2eq}(t)$) making necessary the application of a filter to obtain useful information from signal $z_2(t)$. The filter has to eliminate the high frequency components of such a signal. It can be of the form:

$$p\dot{\bar{z}}_{eq}(t) + \bar{z}_{eq}(t) = z_2(t). \tag{17}$$

Indeed, in [25], it was shown that :

$$\lim_{p \to 0} \bar{z}_{eq}(t) = z_{2eq}(t) \tag{18}$$

Then, by taking a small p it is possible to assume that the equivalent input law (16) is similar to the output of the filter.

4. THE CONSIDERED FAULT SCENARIOS

In this work, the occurrences of faults on inputs of a robot manipulator is considered. In this situation, the real torque applied by the actuators is unknown. That is, $\tau \in \mathbf{R}^n$ being the nominal torque calculated by the robot controller, while $\Delta\tau \in \mathbf{R}^n$ being the input fault, the actual torque vector which is the input of the robotic system, can be written as $\tau(t) = \tau(t) + \Delta\tau(t)$ as shown in Figure 1.

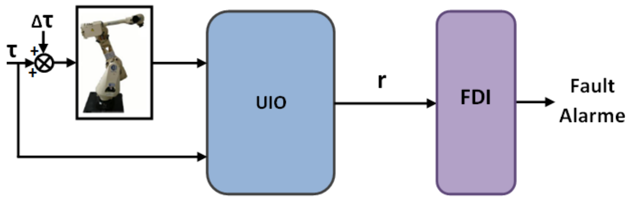


Figure 1. The proposed FDI scheme for actuator faults

5. RESIDUAL GENERATION

Error of the state estimation $r(t)$ can be calculated as:

$$r(t) = \tau(t) - \hat{\tau}(t) \tag{19}$$

The residuals are supposed to differ from zero in the present of faults ($r(t) \neq 0$) and to be zero when there are no faults on the actuators ($r(t) = 0$). So the residuals are defined as:

$$\begin{cases} r(t) = 0 & if \quad \tau = \hat{\tau} \\ r(t) \neq 0 & if \quad \tau \neq \hat{\tau} \end{cases} \tag{20}$$

Table I represents the fault signatures matrix for these residuals. We find that the signatures for each of the failures are quite different.

Table 1. Signature Table for Actuator Fault Isolation

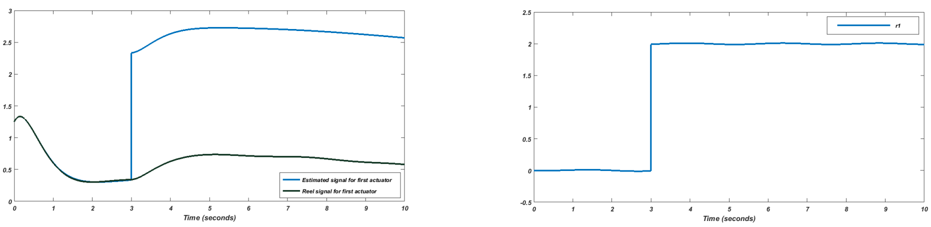
d_i/r_i	r_1	r_2	r_3	r_4	r_5
d_1	1	0	0	0	0
d_2	0	1	0	0	0
d_3	0	0	1	0	0
d_4	0	0	0	1	0
d_5	0	0	0	0	1

6. SIMULATION RESULTS

In this section, the performances of the proposed FDI scheme for robot manipulators are verified, by simulating actuator faults. To carry out simulations, the model (5) has been simulated together with the observer (10) with the input laws (14) relevant to the Super-Twisting approach. The presence of actuator faults $\Delta\tau$ is simulated by introducing an abrut fault signal on the different articulation of the robot (joint 1, 2, 3, 4, 5, respectively). The simulation shows fault detection and isolation for the five articulations of robot manipulators. Detection and isolation of the faults for actuators ($\Delta\tau$ and $\Delta\hat{\tau}$ signals) by using the Super-Twisting input law. Figures 2, 3, 4, 5, 6 presents two signals, one for the actual states and the other for the estimated states. Figures are simulated during the time of $T = 10s$. The kind of fault is "Abrut". the difference between the two signals gives a residual for each joint of the system.

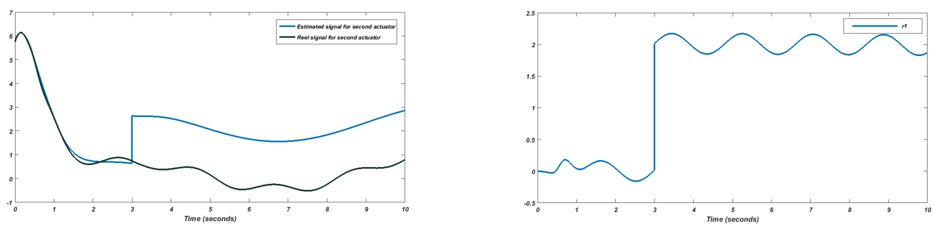
Figure (b) in figures 2, 3, 4, 5, 6 shows an observation error between the actual states and the estimated states. Residuals for all articulations are different from each other and react according to signature table for actuator fault isolation. The fault is appeared at the time $t = 3s$.

This methods gives a good results in comparison between the original state and the state estimate, therefore the state estimate converges to the actual state rapidly, that's why we find the residuals equal to zero. So this proposed technique detect and isolate the actuator faults in a robot manipulator.



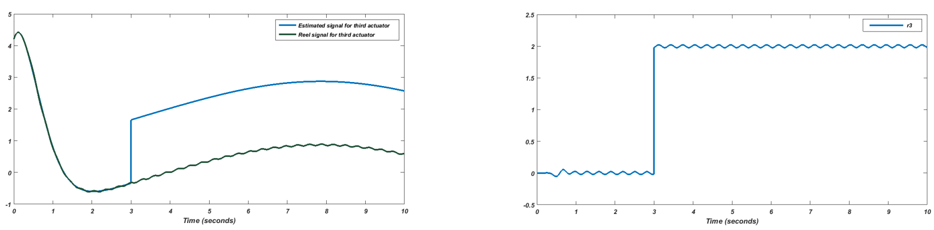
(a) Fault signal reconstruction (b) Residual signal for the first actuator

Figure 2. Simulation of FDI on the first actuator ($\Delta\tau$ and $\Delta\hat{\tau}$ signals). Detection and isolation of the faults by using the Super-Twisting input law.



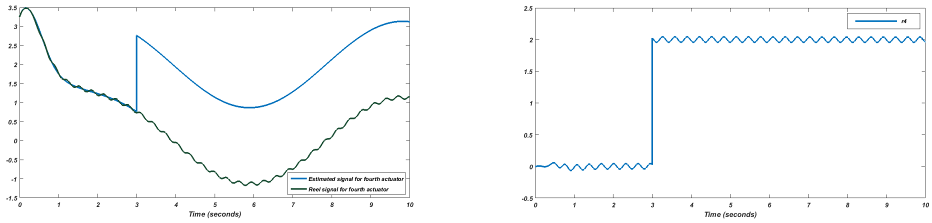
(a) Fault signal reconstruction (b) Residual signal for the second actuator

Figure 3. Simulation of FDI on the second actuator ($\Delta\tau$ and $\Delta\hat{\tau}$ signals). Detection and isolation of the faults by using the Super-Twisting input law.



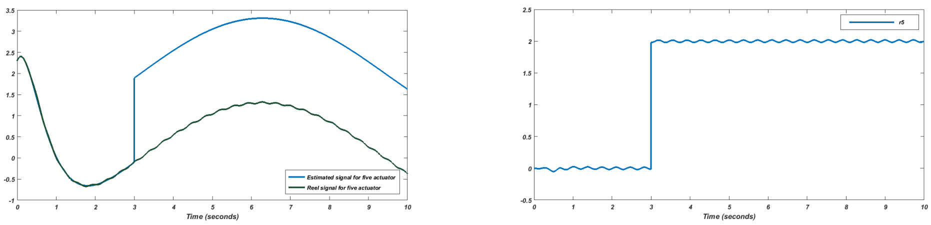
(a) Fault signal reconstruction (b) Residual signal for the third actuator

Figure 4. Simulation of FDI on the third actuator ($\Delta\tau$ and $\Delta\hat{\tau}$ signals). Detection and isolation of the faults by using the Super-Twisting input law.



(a) Fault signal reconstruction (b) Residual signal for the fourth actuator

Figure 5. Simulation of FDI on the fourth actuator ($\Delta\tau$ and $\Delta\hat{\tau}$ signals). Detection and isolation of the faults by using the Super-Twisting input law.



(a) Fault signal reconstruction (b) Residual signal for the five actuator

Figure 6. Simulation of FDI on the five actuator ($\Delta\tau$ and $\Delta\hat{\tau}$ signals). Detection and isolation of the faults by using the Super-Twisting input law.

7. CONCLUSION

The problem of fault detection and isolation on a robot manipulator has been addressed. The presence of fault detection is performed depending on higher order sliding mode Unknown Input Observers (UIOs). The observer input laws are designed by the so called Super-Twisting Second Order Sliding Mode Control (SOSMC). The proposed scheme allows one to detect and isolate faults, even multiple and simultaneous, on the actuators of the robotic system. Simulations are presented proves The effectiveness and the performance of the proposed technique.

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