Higher Order Sliding Mode Observers for Actuator Faults Diagnosis in Robot Manipulators

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***Abstract*—A diagnostic scheme for actuator faults which can occur on a robot manipulator using a model-based Fault Diagnosis (FD) technique is addressed. With the proposed FD scheme it is possible to detect a fault, which can occur on a specific component of the system. To detect 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) approach and they are proved to be capable of guaranteeing the exponential convergence of the fault estimate to the actual fault signal. The proposed approach is verified in simulation and experimentally on a COMAU SMART3-S2 robot manipulator.**

I. Introduction

The electromechanical components of an automatic system are subject to the occurrence of faults. Faults can be caused by particular environmental conditions such as the temperature, the presence of objects in the workspace of the system, usage, bugs in programming, electrical disturbances or unexpected events. The faults can occur in an unpredictable way on a particular component of the system. Some kind of faults can cause critical injuries to the plant operators and to the plant itself. Then, it is fundamental to assure the capability of the diagnostic system to make a prompt detection of these events possible [1]–[3].

The presence of a fault can be modeled as an unexpected change in the system parameters or as the presence of unknown signals in the plant. In a robot manipulator, a fault can occur on a specific actuator, on a specific sensor or on a mechanical component of the system. The occurrence of actuator and sensor faults are more frequent, because of the presence of electrical devices, which may be subject to many possible criticalities.

Diagnostic devices are introduced to generate online diagnostic signals which are useful to detect and isolate the fault presence. The diagnostic signals useful to detect the presence of a fault are usually called *residual signals*. These signals are obtained from the applied system inputs and the measurements. Residual generators are typically based on observers (see, for instance, [4]–[6]). However, noise and uncertainties can reduce the performances of the observers. Particular techniques are adopted in order to overcome this drawback, such as the use of linear filters [6], generalized momenta, see [7], [8], or Kalman filters [9]. These techniques, in the presence of uncertainties typical of practical applications, cannot guarantee an exact convergence of the observer state to the system state. To reduce this problem, sliding mode based techniques are also frequently adopted to accomplish the state observation [10]–[12] because of their design simplicity and robustness features. Usually, the Fault Diagnosis (FD) can be dealt with by combining multiple sliding mode observers [6], [13]–[15].

In this paper, a fault diagnosis scheme to deal with actuator faults in robot manipulators is presented. It is based on Unknown Input Observers (UIO) (see [11], [16], [17]) to detect and identify actuator faults. Robustness of the observers is enhanced by considering as input law of each observer a second order sliding mode law, in particular of *Super-Twisting* type [17]. It can be proved that with this input law, a second order sliding manifold can be reached in finite time, in spite of the uncertainties. As a consequence, the finite time convergence to zero of the observation errors is theoretically guaranteed, which implies the exponential convergence of the fault estimate to the actual fault signal.

Simulation and experimental results are presented in the paper. Comparisons between the results obtained with the proposed scheme and those obtained by applying the Fault Detection scheme proposed in [18] are also presented. Simulations are based on the identified model of a COMAU SMART3-S2 robot manipulator developed in [19], while experiments are made directly on the robot itself.

II. The considered fault scenarios

In this paper, the case of faults occurring on the inputs of a robot manipulator is considered. In this situation, the real torque applied by the actuators is unknown. That is, $\tau \in \mathbb{R}^n$ being the nominal torque calculated by the robot controller, while $\Delta\tau \in \mathbb{R}^n$ being the input fault, the actual torque vector which is the input of the robotic system, can be expressed as $\overline{\tau}(t) = \tau(t) + \Delta\tau(t)$ (see Fig. 1). In practice, faults can be caused by a damage that can occur on power supply systems, or actuator mechanisms, or wirings (but we will not distinguish among them).

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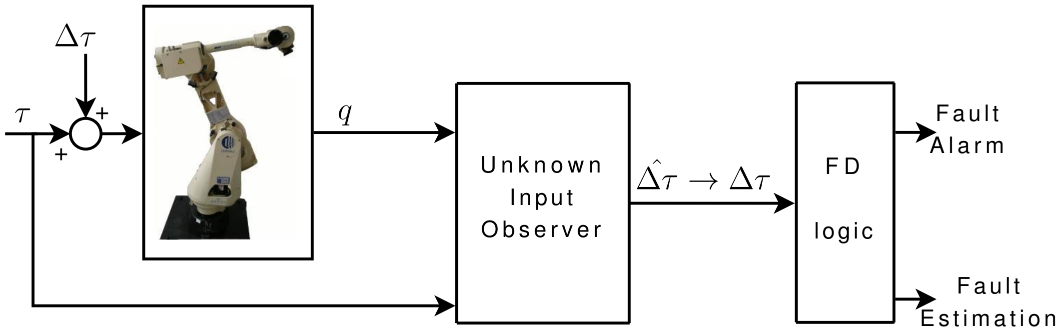

Fig. 1. The proposed FD scheme for actuator faults.

III. THE MANIPULATOR MODEL

In absence of faults, the dynamics of a n-joints robot manipulator can be written in the joint space, by using the Lagrangian approach, as

$$\tau = B(q)\ddot{q} + C(q,\dot{q})\dot{q} + g(q) + F_v\dot{q} = B(q)\ddot{q} + n(q,\dot{q}) \quad (1)$$

(see [20]) where $q \in \mathbb{R}^n$ is the generalized coordinates vector, $B(q) \in \mathbb{R}^{n\times n}$ is the inertia matrix, $C(q,\dot{q})\dot{q} \in \mathbb{R}^n$ represents centripetal and Coriolis torques, $F_v \in \mathbb{R}^{n\times n}$ is the viscous friction diagonal matrix, and $g(q) \in \mathbb{R}^n$ is the vector of gravitational torques. In this paper, it is assumed that the term $n(q,\dot{q})$ in (1) can be identified, while the term $B(q)$ is regarded as known. Now, introducing the variables $\chi_1(t) = q(t)$, $\chi_2(t) = \dot{q}(t)$, model (1) can be rewritten in the state space representation as

$$\begin{cases} \dot{\chi}_1(t) = \chi_2(t) \\ \dot{\chi}_2(t) = f(\tau(t),\chi_1(t),\chi_2(t)) \\ h(t) = \chi_1(t) \end{cases} \quad (2)$$

where the term $f(\tau(t),\chi_1(t),\chi_2(t))$ is obtained after simple algebraic manipulation of (1), i.e.,

$$f(\tau(t),\chi_1(t),\chi_2(t)) = B^{-1}(\chi_1(t))\left(\tau(t) - n(\chi_1(t),\chi_2(t))\right). \quad (3)$$

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

$$\tau(t) + \Delta\tau(t) = B(\chi_1(t))\dot{\chi}_2(t) + n(\chi_1(t),\chi_2(t)) \quad (4)$$

and, as a consequence, the state space representation is

$$\begin{cases} \dot{\chi}_1(t) = \chi_2(t) \\ \dot{\chi}_2(t) = f(\tau(t)+\Delta\tau(t),\chi_1(t),\chi_2(t)) \\ q(t) = \chi_1(t) \end{cases} \quad (5)$$

where $f(\tau(t)+\Delta\tau(t),\chi_1(t),\chi_2(t))$ 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

$$\begin{aligned} f(\chi_1(t),\chi_2(t)) &= B^{-1}(\chi_1(t))(\tau(t)+\Delta\tau(t) \\ &\quad - \hat{n}(\chi_1(t),\chi_2(t)) - \eta(t)), \\ \eta(t) &= n(\chi_1(t),\chi_2(t)) - \hat{n}(\chi_1(t),\chi_2(t)) \end{aligned} \quad (6)$$

where $\eta(t)$ 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 possible (in absence of faults) to determine only an approximated representation of $f(\cdot)$, i.e.

$$\hat{f}(\tau(t),\chi_1(t),\chi_2(t)) = B^{-1}(\chi_1(t))(\tau(t) - \hat{n}(\chi_1(t),\chi_2(t))) \quad (7)$$

so that the actually usable model is

$$\begin{cases} \dot{\chi}_1(t) = \chi_2(t) \\ \dot{\chi}_2(t) = \hat{f}(\tau(t)+\Delta\tau(t),\chi_1(t),\chi_2(t)) \\ q(t) = \chi_1(t). \end{cases} \quad (8)$$

IV. 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 [3], [21]. In this paper, we propose to detect the actuator faults by means of UIOs of sliding mode type. The proposed UIOs can be jointly described as a multi-input-multi-state second order sliding mode observer, as shown in the next subsection.

A. Observer Design

Let us consider the observer

$$\begin{cases} \dot{\hat{\chi}}_1(t) = \hat{\chi}_2(t) + z_1(t) \\ \dot{\hat{\chi}}_2(t) = \hat{f}(\tau(t),\chi_1(t),\hat{\chi}_2) + z_2(t) \end{cases} \quad (9)$$

where $\hat{\chi}_1(t), \hat{\chi}_2 \in \mathbb{R}^{2n}$ 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 in order to 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.

B. Dynamics of the Observer Error

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

$$\begin{cases} e_1(t) = \chi_1(t) - \hat{\chi}_1(t) \\ e_2(t) = \chi_2(t) - \hat{\chi}_2(t). \end{cases} \quad (10)$$

By steering to zero these quantities, it is possible to guarantee that the observer (9) 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,

$$\begin{cases} \dot{e}_1(t) = e_2(t) - z_1(t) \\ \dot{e}_2(t) = f(\tau(t), \chi_1(t), \chi_2(t)) \\ \qquad - \hat{f}(\tau(t) + \Delta\tau(t), \chi_1(t), \hat{\chi}_2(t)) - z_2(t) \end{cases} \tag{11}$$

which can be rewritten as

$$\begin{cases} \dot{e}_1(t) = e_2(t) - z_1(t) \\ \dot{e}_2(t) = B^{-1}(\chi_2(t))(\Delta\tau(t) - \eta(t)) - z_2(t). \end{cases} \tag{12}$$

Now, two different Second Order Sliding Mode approaches are studied to design the multi-input-multi-state UIO input law. The first approach is the so-called Super-Twisting [17], while the second approach is based on the so-called Sub-Optimal algorithm. More precisely, the second approach is applied to have the possibility of making a performance comparison. The two proposals will be depicted in the next subsections.

C. 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

$$\begin{cases} z_1(t) = \lambda\sqrt{|s'(t)|}\text{sign}(s'(t)) \\ z_2(t) = \alpha\text{sign}(s'(t)) \end{cases} \tag{13}$$

where $s'(t) = e_1(t) = \chi_1(t) - \hat{\chi}_1(t)$. 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

$$\begin{cases} e_1(t) = 0 \\ e_2(t) = 0 \end{cases} \tag{14}$$

is guaranteed in finite time (the proof of this claim can be developed as in [17]). To implement the proposed procedure, the terms α and λ have been choosen 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 (12) can be rewritten as

$$z_{2eq}(t) = B^{-1}(\chi_2(t))(\Delta\tau(t) - \eta(t)) \tag{15}$$

where $z_{2eq}(t)$ is the equivalent input signal corresponding to the discontinuous signal $z_2(t)$, see [23]. Thus, theoretically, the equivalent input signal is the result of an infinite switching frequency of the discontinuous term $\alpha\text{sign}(s'(t))$. In fact, the implementation of the observer produces high switching frequency (since, in practice, one can only implement $z_2(t)$ as in (13) 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

$$p\dot{\overline{z}}_{eq}(t) + \overline{z}_{eq}(t) = z_2(t). \tag{16}$$

Indeed, in [24] and [25], it was shown that

$$\lim_{p\to 0} \overline{z}_{eq}(t) = z_{2eq}(t), \quad p \in \mathbb{R}$$

Then, by taking a small p it is possible to assume that the equivalent input law (15) is similar to the output of the filter.

D. Sub-Optimal Algorithm based Observer

The observer input laws of Sub-Optimal type are given by

$$\begin{cases} z_1(t) = 0 \\ \dot{z}_2(t) = \alpha' W_{MAX}\text{sign}\left\{s''(t) - 0.5 s''_{MAX}\right\} \\ z_2(0) = 0 \end{cases} \tag{17}$$

where $s''(t) = e_2(t) + \beta e_1(t)$ is the sliding variable and, in this case, s''_{MAX} represents the last extremal value of the sliding variable $s''(t)$, and $\beta > 0$. It can be proved that a suitable choice of $\alpha' W_{MAX}$ exists such that the Sub-Optimal input laws guarantee the exponential stability of the tracking error of this observer (the proof of this claim can be developed as in [26]). Also in this case, in practice, α' and W_{MAX} are choosen relying on an experimental tuning procedure.

E. Residual Generation for Actuator Faults

The residual signal considered for fault diagnosis is obtained in both cases from the input law $z_2(t)$.

Let the following 5$^{\text{th}}$ order low-pass filter be introduced (s is the Laplace operator)

$$\mathcal{F}(s) = \frac{b}{1 - as^{-1} - as^{-2} - as^{-3} - as^{-4} - as^{-5}}. \tag{18}$$

The residual signal useful to detect actuator faults is given by

$$r_i(t) = \begin{cases} 0 & \text{if} \quad |\ \ell(t) * B(q(t))z_{2i}(t)\ | < T_i \\ 1 & \text{if} \quad |\ \ell(t) * B(q(t))z_{2i}(t)\ | > T_i \end{cases} \quad \forall\, i \tag{19}$$

where $\ell(t)$ indicates the impulse response of $\mathcal{F}(s)$, $*$ indicates the convolution product, and T_i are suitable thresholds chosen on the basis of the amplitude of the noise which is present on the system. More specifically, the maximum amplitude of the typical noise signal has been estimated during the experiments and the thresholds have been determined so as to slightly overcome this amplitude.

F. Identification of the Actuator Faults Signals

The input signal $z_2(t)$, independently of the type of the observer adopted, between the two proposals previously described, is useful also to give an estimation of the shape of the fault signal $\Delta\tau$. That is, the estimation $\widehat{\Delta\tau}$ of the input fault $\Delta\tau$ is given by

$$\widehat{\Delta\tau} = \ell(t) * B(q(t))z_2(t) \tag{20}$$

and $z_{2i}(t)$ can be obtained from both (13) or (17).

The following theorems are proved.

Theorem IV.1 (Convergence of the $\widehat{\Delta\tau}$ to $\Delta\tau$ by using the Super-Twisting input laws)**.** *Using the input laws (13) in the observer (9), a choice of the terms α and λ exists such that the* *condition $[e_1(t), e_2(t)]^T = \underline{0}$, $\underline{0}$ being the null vector $\in \mathbb{R}^2$, is reached in finite time. Then, in absence of noise $\eta(t)$, the signal $\widehat{\Delta\tau}$ converges to $\Delta\tau$ exponentially.*

Proof: The proof that the condition $[e_1(t), e_2(t)]^T = \underline{0}$ is achieved in finite time can be developed as in [17] (see Theorem 1). Once the condition

$$e_2(t) = \chi_2(t) - \hat{\chi}_2(t) = 0 \tag{21}$$

is established, one has also that, by virtue of the existence of the so-called equivalent control, which is obtained by filtering $z_2(t)$ in (20) with the filter (18) (see [24], [22], and [25]), the signal $\widehat{\Delta\tau}$ converges to $\Delta\tau$ exponentially. ■

A similar result can be established for the Sub-Optimal input law (17).

Theorem IV.2 (Convergence of the $\widehat{\Delta\tau}$ to $\Delta\tau$ by using the Sub-Optimal input laws)**.** *Using the input laws (17) in the observer (9), a choice of the terms W_{iMAX} and α^* exists such that the observer error state vector $[e_1(t), e_2(t)]^T$ reaches the origin exponentially. Then, in absence of noise $\eta(t)$, the signal $\widehat{\Delta\tau}$ converges to $\Delta\tau$ exponentially.*

Proof: The proof that the condition $[e_1(t), e_2(t)]^T = \underline{0}$ is achieved exponentially can be developed as in [26] and [27] (see theorems 1 and 2, respectively). Since

$$\lim_{t\to\infty} e_2(t) = 0 \tag{22}$$

i.e.,

$$\lim_{t\to\infty} \chi_2(t) - \hat{\chi}_2(t) = 0 \tag{23}$$

one has also that

$$\lim_{t\to\infty} \dot{\chi}_2(t) - \dot{\hat{\chi}}_2(t) = 0 \tag{24}$$

then,

$$\lim_{t\to\infty} z_2(t) = B^{-1}(q(t))\Delta\tau(t). \tag{25}$$

Finally, by using the filter (18), one has

$$\widehat{\Delta\tau}(t) \to \Delta\tau(t) \tag{26}$$

■

V. A Case Study

A. The considered manipulator

The fault diagnosis technique described in this paper has been experimentally verified on a COMAU SMART3-S2 anthropomorphic rigid robot manipulator which is a classical example of industrial manipulator (see Fig. 2). It consists of six links and six rotational joints driven by brushless electric motors.

For the sake of simplicity during the experiments the robot has been constrained to move on a vertical plane. Then, it is possible to consider the robot as a three link-three joint, in the sequel numbered as $\{1, 2, 3\}$, planar manipulator (see Fig. 2). Yet, the method proposed in this paper holds for n-joints robots even of spatial type.

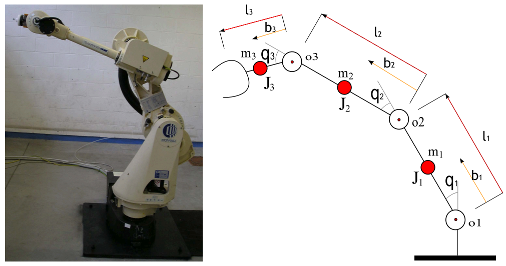

Fig. 2. The SMART3-S2 robot and the three link planar manipulator.

The controller has a sampling time of 0.001[s], a 12 bit D/A and a 16 bit A/D converters. The joints positions are acquired by resolvers fastened on the three motors, holding mechanical reducers with ratio $\{207, 60, 37\}$ respectively, while the maximum torques are $\{1825, 528, 71\}$[Nm].

B. Parameters identification

The adopted identification procedure is based on the Maximum Likelihood (ML) approach, as explained in [19] (in the absence of faults). To perform the identification, the dynamical model (1) can be written in the following form

$$Y = \Phi(q, \dot{q}, \ddot{q})\theta^o + V \tag{27}$$

where the nonlinear matrix function $\Phi(\cdot) \in \mathbb{R}^{3N\times 9}$ represents model (1) in a parametrized linear form, N being the number of sampled data, and 3 being the number of the considered joints. The term $\theta^o = [\gamma_1 \dots \gamma_9]^T$, $\gamma_i \in \mathbb{R}$, represents the unknown parameter vector to be estimated, while $Y \in \mathbb{R}^{3N}$ is the torque applied by the actuators, and $V \in \mathbb{R}^{3N}$ is the noise acting on Y, which is the input of the robotic system. The parametrization of θ^o is shown in Table I, see [19], while in Table II the values of the identified parameters for the considered robot are reported (expressed in SI units).

Parameter	Meaning
γ_1	$m_3 b_3^2 + J_3$
γ_2	$J_3 + m_3(l_2^2 + b_3^2) + J_2 + m_2 b_2^2$
γ_3	$J_3 + m_3(l_1^2 + l_2^2 + b_3^2) +$
	$J_2 + m_2(l_1^2 + b_2^2) + J_1 + m_1 b_1^2$
γ_4	$m_1 b_1 + m_2 l_1 + m_3 l_1$
γ_5, γ_6	$m_2 b_2 + m_3 l_2,\ m_3 b_3$
$\gamma_7, \gamma_8, \gamma_9$	F_{v1}, F_{v2}, F_{v3}

TABLE I
PARAMETRIZATION OF THE MANIPULATOR MODEL.

θ^{ML}	γ_1	γ_2	γ_3	γ_4	γ_5
$E[\theta^{ML}]$	0.297	10.07	87.91	57.03	9.21
$Var[\theta^{ML}]$	0.003	0.04	0.2	0.06	0.02
θ^{ML}	γ_6	γ_7	γ_8	γ_9	
$E[\theta^{ML}]$	0.316	66.3	14.71	8.29	
$Var[\theta^{ML}]$	0.003	0.3	0.1	0.02	

TABLE II
AVERAGE VALUE AND VARIANCE FOR THE ESTIMATED PARAMETERS.

C. The manipulator control algorithm

To carry on the experiments on the COMAU SMART3-S2 manipulator it is necessary to control the robot. A particular control scheme is considered in this work, which consists of an inverse dynamics control performing a non ideal feedback linearization, combined with a robust second order sliding mode controller of Sub-Optimal type, the application of which to a COMAU SMART3-S2 manipulator has already been described in [27].

VI. Simulation Results

In this section, the performances of the proposed FD scheme for robot manipulators are verified, by simulating actuator faults. Note that random noise with variance equal to 1[N^2m^2] is added on the input signals, in order to make the simulations be more realistic. To carry out simulations, a discrete version of model (5) has been implemented together with the discrete version of the observer (9) with the input laws (13) relevant to the Super-Twisting approach.

The presence of actuator faults $\Delta\tau$ is simulated by introducing a sinusoidal fault signal on the first component of $\Delta\tau$ (which is relevant to joint 1) and by introducing two abrupt fault signals on the second and third components of $\Delta\tau$ (which are relevant to joint 2 and 3, respectively). As one can see from Fig. 3, 4, 5, the fault shapes are correctly identified.

Note that the presence of the three actuator faults in simulation is simultaneous. As can be seen in Fig. 3, the thresholds are violated for a short time when the fault occurs on actuator 2, which shows the obvious existence of a slight interaction among the system components.

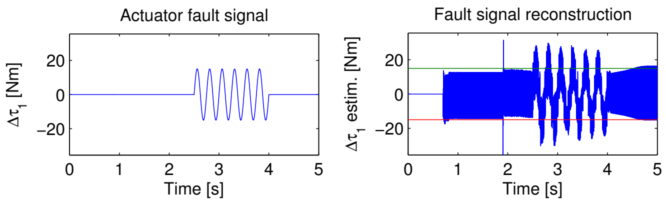

Fig. 3. Simulation of FD and fault identification on the first actuator ($\Delta\tau$ and $\widehat{\Delta\tau}$ signals). Detection and identification of the faults by using the Super-Twisting input law.

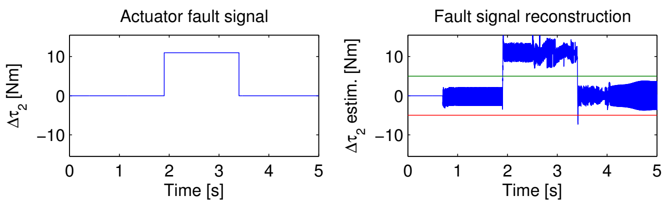

Fig. 4. Simulation of FD and fault identification on the second actuator ($\Delta\tau$ and $\widehat{\Delta\tau}$ signals). Detection and identification of the faults by using the Super-Twisting input law.

VII. Experimental Results

In this section the proposed scheme is experimentally tested on the COMAU SMART3-S2 manipulator. The faults presence is introduced in the control system by adding a fault signal to the 3-dimensional control variable.

More specifically, the case of abrupt faults on the actuators of each joint is considered, that is a -50[Nm] fault signal acting on the first actuator, a -20[Nm] fault signal acting on

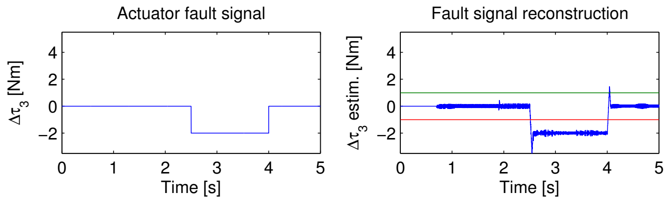

Fig. 5. Simulation of FD and fault identification on the third actuator ($\Delta\tau$ and $\widehat{\Delta\tau}$ signals). Detection and identification of the faults by using the Super-Twisting input law.

the second actuator, and a -10[Nm] fault signal acting on the third actuator are considered. Note that these faults signals are approximatively the 20% of the maximum torque allowed by the corresponding actuator. As can be seen from Fig. 6-8 for the Super-Twisting UIOs and from Fig. 9-11 for the Sub-Optimal UIOs, the fault signals are correctly detected, isolated, and identified. The Super-Twisting approach, as for the fault occurred on the first and second actuators, provides better performances, while as for the fault occurred on the third actuator, the Sub-Optimal approach shows a superior capability to avoid false alarms.

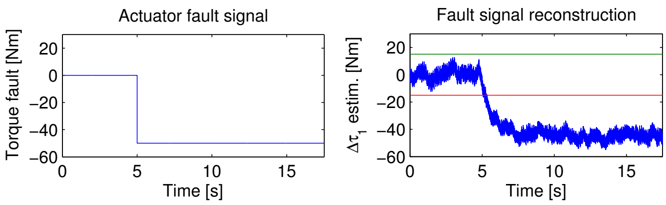

Fig. 6. FD experiment on the first actuator ($\Delta\tau$ and $\widehat{\Delta\tau}$ signals). Detection and identification of the faults by using the Super-Twisting input law.

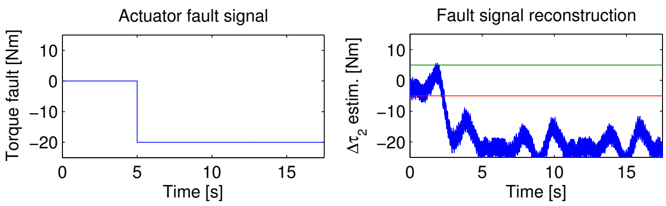

Fig. 7. FD experiment on the second actuator ($\Delta\tau$ and $\widehat{\Delta\tau}$ signals). Detection and identification of the faults by using the Super-Twisting input law.

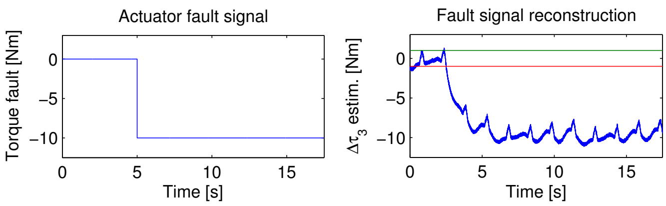

Fig. 8. FD experiment on the third actuator ($\Delta\tau$ and $\widehat{\Delta\tau}$ signals). Detection and identification of the faults by using the Super-Twisting input law.

VIII. Conclusions

The problem of finding and isolating faults which can occur on a robot manipulator has been addressed. A diagnostic scheme for actuator faults has been proposed. The proposed

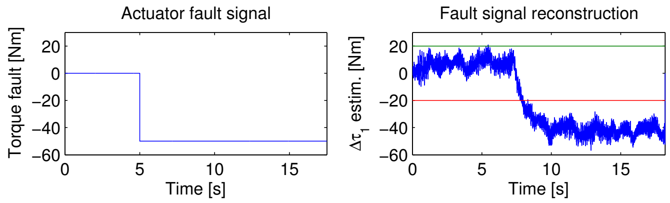

Fig. 9. FD experiment on the first actuator ($\Delta\tau$ and $\widehat{\Delta\tau}$ signals). Detection and identification of the faults by using the Sub-Optimal input law.

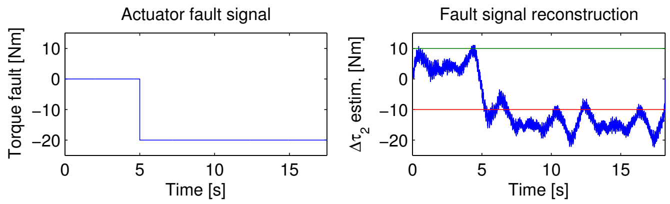

Fig. 10. FD experiment on the second actuator ($\Delta\tau$ and $\widehat{\Delta\tau}$ signals). Detection and identification of the faults by using the Sub-Optimal input law.

scheme allows one to detect and isolate faults, even multiple and simultaneous, on the actuators of the robotic system. The detection of the faults presence is performed relying on higher order sliding mode Unknown Input Observers (UIOs). The observer input laws are designed according to the so-called Super-Twisting Second Order Sliding Mode Control (SOSMC). Simulations and experimental results on a real COMAU SMART3-S2 are presented in order to compare the proposed approach with a previously proposed approach, which relies on the so-called Sub-Optimal Second Order Sliding Mode Control (SOSMC).

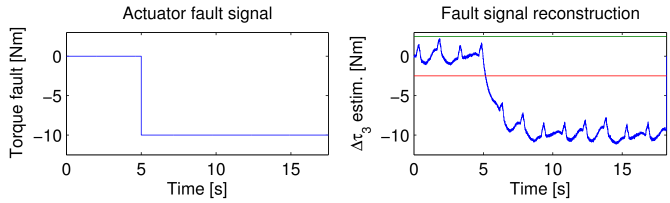

Fig. 11. FD experiment on the third actuator ($\Delta\tau$ and $\widehat{\Delta\tau}$ signals). Detection and identification of the faults by using the Sub-Optimal input law.

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