Manipulator Fault Diagnosis via Higher Order Sliding-Mode Observers

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***Abstract*—A diagnostic scheme for actuator and sensor 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 are proposed to provide the necessary analytical redundancy. The detection of sensor faults, instead, is made by relying on a generalized observer scheme. The observer input laws are designed according to two well-known second-order sliding-mode approaches: the so-called supertwisting and the suboptimal one. Both typologies of input laws allow to perform a satisfactory FD. The peculiarities of each input law of the observers are discussed. To make possible fault isolation, it is required that a single fault acts only on one component of the system at a time. If one knows that faults occurred only on actuators, then it is possible to isolate multiple simultaneous faults on actuators. The proposed approach is verified in simulation and experimentally on a COMAU SMART3-S2 robot manipulator.**

***Index Terms*—Fault diagnosis, fault location, generalized observer scheme, manipulators, robots, robustness, variable structure systems.**

I. Introduction

INDUSTRIAL plants and consumer devices often have crucial applications in everyday life. The increasing possibility of reducing the efforts needed by the people to manage and to monitor them is an important challenge. To comply with this challenge, the controllers of these plants should be able to operate also in critical conditions, i.e., when the behavior of some components of the systems is significantly different from the expected behavior. Faults can be caused by particular environmental conditions and by plant conditions itself. They can occur in an unpredictable way on a particular component of the system. Some kinds of faults can cause critical injuries to the plant operators and to the plant itself. Then, it is fundamental to include in the controller a block dedicated to diagnose the system. This block should have the capability to make a prompt detection of the fault events [1], [5], [6].

The presence of a fault can be modeled as an unexpected change in the dynamics of the system, 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 is more frequent because of the presence of electrical devices, which may be subject to many possible critical situations.

Diagnostic devices are introduced to generate online diagnostic signals which are useful to detect and isolate the fault. 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, [2], [7]–[10]). 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 [9], generalized momenta, see [11], or Kalman filters [12]. These techniques, in the presence of the 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 [13], [14] because of their design simplicity and robust features. Usually, the fault diagnosis (FD) can be dealt with by combining multiple sliding-mode observers as discussed in [9], [15]–[18]. Stochastic-based observers can be considered to obtain the residual signals (see [19]). These have proved capabilities to compensate for the effects of noise and are particularly robust for FD in a networked environment. Moreover, stochastic observers succeed more accurate estimation and exhibit the smoother variations of the estimation error.

In this paper, an FD scheme to deal with actuator faults or with sensor faults in robot manipulators is considered. It is based on unknown input observers (UIOs) (see [3], [13], [20]–[24]) to detect actuator faults and on a generalized observer scheme (GOS) to detect sensor faults. While the UIO approach is specifically designed to obtain a suitable estimation of an unknown signal present on the inputs of the system, which can be produced by a fault, the detection of unknown signals which affect the outputs of the system is more difficult because of the lack of the observability properties typical of the robotic

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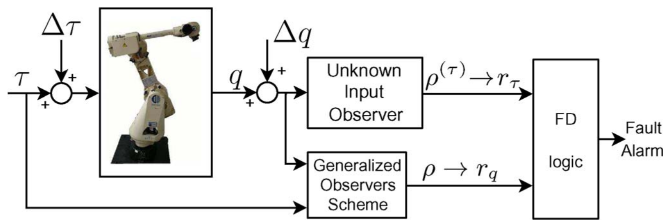

Fig. 1. Proposed FD scheme for actuator and sensor faults.

systems, see [18]. The adopted GOS allows to improve the observability properties.

The objective of this paper is to study the performance in terms of the robustness and diagnostic capabilities of two possible sliding-mode input laws for the observers. In particular, two second-order sliding mode (SOSM) laws, the *supertwisting* law [21] and the *suboptimal* one [25], are considered. The reason why an SOSM input law turns out to be an effective choice to solve the problem under concern is due to the necessity of coming up with continuous observer input laws, so that such laws can be used as signals upon which the diagnostic procedure is directly based. The diagnostic scheme proposed in this paper proves to be able to detect nonsimultaneous sensor and actuator faults and, in some cases, also provides good isolation and identification capabilities independent from the specific SOSM input law which is adopted.

The analysis of both approaches confirms the good features of both algorithms, as well as their suitability to be applied in the FD context. Moreover, it also puts into evidence some peculiarities of the two, which can help the user to select between them depending on the specific needs of the considered case. Experimental results are presented in this paper for an industrial manipulator.

II. Considered Fault Scenarios

In this paper, the case of faults occurring on the inputs or on the outputs of a robot manipulator is considered. In the first case, 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 $\tau(t) + \Delta\tau(t)$ (see Fig. 1). In the case of sensor faults, the control system cannot determine the exact angular displacements of the joints. Let $q \in \mathbb{R}^n$ be the true but unknown output (i.e., the joint displacements) while $\Delta q \in \mathbb{R}^n$ be the vector of the fault signals acting on it. Then, $\bar{q} \in \mathbb{R}^n$ represents the value that the control system receives, i.e., $\bar{q}(t) = q(t) + \Delta q(t)$ (see Fig. 1).

III. Manipulator Model

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

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

where $q \in \mathbb{R}^n$ is the generalized coordinate vector, $B(q) \in R^{n\times n}$ 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 $n(q,\dot{q})$ can be identified, while the term $B(q)$ is regarded as known.

Now, introducing the variables $\chi_1(t) = q(t)$ and $\chi_2(t) = \dot{q}(t)$, when faults affect either the actuators or the sensors, model (1) can be rewritten in the state-space representation as

$$\begin{cases} \dot{\chi}_1(t) = \chi_2(t) \\ \dot{\chi}_2(t) = \hat{f}\left(\tau(t) + \Delta\tau(t), \chi_1(t), \chi_2(t)\right) \\ \bar{q}(t) = \chi_1(t) + \Delta q(t) \end{cases} \quad (2)$$

where $\hat{f}(\cdot)$ is obtained after an identification procedure such as the one proposed in [4] and it is given by

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

and $\hat{n}(q,\dot{q})$ is the known part of the model such that $\eta(t) = n(\chi_1,\chi_2) - \hat{n}(\chi_1,\chi_2)$. The term $\eta(t)$ is uncertain but can be assumed to be bounded since, in real applications, the terms q and $\dot{q}$ are bounded, see [27].

IV. Actuators FD Strategy

By relying on the so-called UIO approach [13], the efficient estimators of the input torques can be designed [6], [28]. In this paper, we propose to detect the actuator faults by means of the UIOs of sliding-mode type as shown in the next subsection.

A. Observer Design

Let us consider the observer

$$\begin{cases} \dot{\hat{\chi}}_1(t) = \hat{\chi}_2(t) + z_1(t) \\ \dot{\hat{\chi}}_2(t) = \hat{f}\left(\tau(t), \chi_1(t), \hat{\chi}_2(t)\right) + z_2(t) \end{cases} \quad (4)$$

where $\hat{\chi}_1(t) \in \mathbb{R}^n$ and $\hat{\chi}_2(t) \in \mathbb{R}^n$ are the observer states and $z(t) = [z_1(t), z_2(t)]^{\mathrm{T}}$ is an auxiliary input signal, which is designed relying on a sliding-mode approach. This signal is introduced in order to guarantee the convergence of the observer states to the actual state of the system.

B. Dynamics of the Observer Error

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

$$\begin{cases} e_1(t) = \chi_1(t) - \hat{\chi}_1(t) \\ e_2(t) = \chi_2(t) - \hat{\chi}_2(t). \end{cases} \quad (5)$$

By steering to zero these quantities, it is possible to guarantee that the observer (4) gives a good estimation of the unknown input. The dynamics of the error variable $e(t)$ is represented by a second-order dynamical system

$$\begin{cases} \dot{e}_1(t) = e_2(t) - z_1(t) \\ \dot{e}_2(t) = B^{-1}\left(\chi_1(t)\right)\left(\Delta\tau(t) - \eta(\chi_1,\chi_2,\hat{\chi}_2)\right) - z_2(t). \end{cases} \quad (6)$$

Now, two different SOSM approaches are exploited to design the multi-input-multistate UIO input law. The first approach is the so-called supertwisting algorithm [21], while the second is the so-called suboptimal algorithm.

C. Supertwisting-Based Observer

The design of the observer input laws which are the components of $z(t) = [z_1(t), z_2(t)]^{\mathrm{T}}$ using a supertwisting-based approach (see [21]) is given by

$$\begin{cases} z_1(t) = \lambda\sqrt{|\sigma'(t)|}\mathrm{sign}\left(\sigma'(t)\right) \\ z_2(t) = \alpha\mathrm{sign}\left(\sigma'(t)\right) \end{cases} \tag{7}$$

where $\sigma'(t) = e_1(t) = \chi_1(t) - \hat{\chi}_1(t)$ and on the basis of [21], the selection of parameters α and λ can be made, taking into account the constraints

$$\alpha > f^+, \lambda > \sqrt{\frac{2}{\alpha - f^+}\frac{(\alpha + f^+)(1+\nu)}{(1-\nu)}} \tag{8}$$

where f^+ is an upper bound of the term $\eta(\chi_1, \chi_2, \hat{\chi}_2)$, which, in our case, has been experimentally determined and ν is a constant, $0 < \nu < 1$.

Note that the term $z_2(t)$ is a discontinuous signal, and by the virtue of the filtering action considered in [21], the second equation of the system (6) can be rewritten as

$$z_{2\mathrm{eq}}(t) = B^{-1}\left(\chi_1(t)\right)\left(\Delta\tau(t) - \eta(t)\right) \tag{9}$$

where $z_{2\mathrm{eq}}(t)$ is the equivalent input signal corresponding to the discontinuous signal $z_2(t)$, see [29]. Thus, theoretically, the equivalent input signal is the result of an infinite switching frequency of the discontinuous term $\alpha\mathrm{sign}(\sigma'(t))$. In fact, the implementation of the observer produces high switching frequency 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. In [30] and [31], it is shown that it is possible to assume that the equivalent input law (9) is equivalent to a filter output.

D. Suboptimal-Algorithm-Based Observer

The observer input laws of the suboptimal type are given by

$$\begin{cases} z_1(t) = 0, \quad z_2(0) = 0 \\ \dot{z}_2(t) = \delta W \mathrm{sign}\left\{\sigma''(t) - 0.5\sigma''_M\right\} \end{cases} \tag{10}$$

where $\sigma''(t) = e_2(t) + \beta e_1(t)$ is the sliding variable; in this case, σ''_M represents the last extremal value of the sliding variable $\sigma''(t)$; and $\beta > 0$. The last extremal value of the sliding variable $\sigma''(t)$ revealed before time instant t can be found following two possible approaches: the peak-detection algorithm proposed in [25] and [32] or considering the output of a second-order robust-differentiator algorithm, see [33].

It can be proved that a suitable choice of δW exists such that the suboptimal input laws guarantee the exponential stability of the tracking error of this observer. In (10), on the basis of [25], the selection of parameters W and δ can be made, taking into account the constraints

$$W > \max\left(\frac{f^+}{\alpha^*}; \frac{4f^+}{3-\alpha^*}\right), \quad f^+ > |\eta|, \quad \alpha^* > 0$$

$$\delta_i = \begin{cases} \alpha^* & \text{if } \left[\sigma''(t) - 0.5\sigma''_M\right], \left[\sigma''_M - \sigma''^{(t)}\right] > 0 \\ 1 & \text{if } \left[\sigma''(t) - 0.5\sigma''_M\right], \left[\sigma''_M - \sigma''^{(t)}\right] \le 0. \end{cases} \tag{11}$$

E. Residual Generation for Actuator Faults

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

As previously stated, to obtain suitable residual signals from the discontinuous signals of the observers, it is necessary to apply a filter. Let us consider the following fifth-order low-pass filter (s is the Laplace operator):

$$\mathcal{F}(s) = \frac{b}{1 - as^{-1} - as^{-2} - as^{-3} - as^{-4} - as^{-5}} \tag{12}$$

where $a = 0.1961$ and $b = 15a$ have been chosen after an experimental tuning procedure.

The residual signal useful to detect actuator faults is given by

$$r_i(t) = \begin{cases} 0 & \text{if } \left|\ell(t) * B\left(q(t)\right) z_{2i}(t)\right| < T_i \\ 1 & \text{if } \left|\ell(t) * B\left(q(t)\right) z_{2i}(t)\right| > T_i \end{cases} \quad \forall i \tag{13}$$

where $\ell(t)$ indicates the impulse response of $\mathcal{F}(s)$, $*$ indicates the convolution product, and T_i denotes suitable thresholds chosen on the basis of the amplitude of the noise which is present on the system.

F. Identification of the Actuator-Fault Signals

The input signal $z_2(t)$, independent of the type of the input law adopted between the two proposals previously described, is also useful 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

$$\widehat{\Delta\tau} = \ell(t) * B\left(q(t)\right) z_2(t) \tag{14}$$

and $z_2(t)$ can be obtained from both (7) and (10). The term $\eta(t)$ is just neglected in the present work, and no further considerations on its bounds are proposed for robustness purposes. Additionally, the choice of the thresholds is based on the experimental determination of upper bounds on noise and unmodeled effects. The proposals of the choices of the thresholds, for instance, based on optimality criteria, can be found in [34].

Theorem IV.1 (Convergence of the $\widehat{\Delta\tau}$ to $\Delta\tau$ by Using the Supertwisting Input Laws): Using the input laws (7) in the observer (4), a choice of the terms α and λ exists according to (8) such that the condition $[e_1(t), e_2(t)]^{\mathrm{T}} = \underline{0}$, $\underline{0}$ being the null vector $\in \mathbb{R}^{2n}$, is reached in finite time. Then, in the absence of noise $\epsilon(t)$, the signal $\widehat{\Delta\tau}$ converges to $\Delta\tau$ exponentially.

The condition $[e_1(t), e_2(t)]^{\mathrm{T}} = \underline{0}$ is achieved in finite time as it was developed in [21, Th. 1].

A similar result can be established for the suboptimal input law (10).

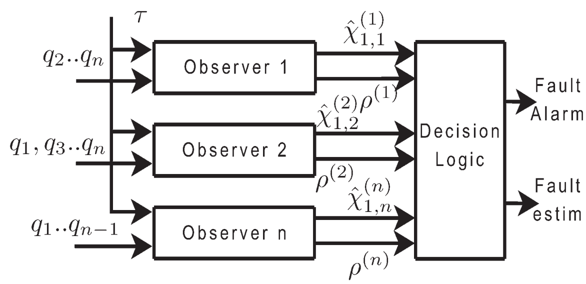

Fig. 2. GOS for an n sensor system.

Theorem IV.2 (Convergence of the $\widehat{\Delta\tau}$ to $\Delta\tau$ by Using the Suboptimal Input Laws): Using the input laws (10) in the observer (4), a choice of the terms W_{iM} and α^* exists according to (11) such that the observer-error state vector $[e_1(t), e_2(t)]^{\mathrm{T}}$ reaches the origin exponentially. Then, in the absence of noise $\epsilon(t)$, the signal $\widehat{\Delta\tau}$ converges to $\Delta\tau$ exponentially.

The proof that the condition $[e_1(t), e_2(t)]^{\mathrm{T}} = \underline{0}$ is achieved exponentially was developed in [25, Th. 1] and [27, Th. 2].

V. Sensor FD Strategy

To perform the detection of sensor faults, n observers are used, one for each sensor (see Fig. 2). This strategy, called GOS [8], and the proposed particular implementation are described in this section.

In the sequel, the following notation is considered for the vectors used in the GOS observers: $\hat{\chi}_1^{(i)} \in \mathbb{R}^n$ is the vector of the estimate of the $\bar{q}$ vector made by the ith observer, $e^{(i)} \in \mathbb{R}^n$ contains the corresponding observation errors, while $\rho^{(i)} \in \mathbb{R}^n$ is the input law of observer i. Moreover, the components of $\hat{\chi}_1^{(i)}$ are $\hat{\chi}_1^{(i)} = [\hat{\chi}_{1,1}^{(i)}\ \hat{\chi}_{1,2}^{(i)}\ \cdots\ \hat{\chi}_{1,n}^{(i)}]^{\mathrm{T}},\ i = 1, \ldots, n$. Now, the ith GOS observer in our proposal is defined as

$$\begin{cases} \dot{\hat{\chi}}_1^{(i)} = \hat{\chi}_2^{(i)} + z_1^{(i)}(t) \\ \dot{\hat{\chi}}_2^{(i)} = \hat{f}\left(\hat{\chi}_1^{(i)}, \hat{\chi}_2^{(i)}, \tau\right) + \rho^{(i)}(t). \end{cases} \tag{15}$$

In contrast to the actuator FD, for which a single observer is used, for sensor FD, n sliding-mode observers are designed.

Then, also in this case, we design the input laws $z_1^{(i)}(t)$ and $\rho^{(i)}(t)$ of each observer in (15) with the suboptimal and supertwisting algorithms. Posing the ith component of $z_1^{(i)}(t)$ and $\rho^{(i)}(t)$ equal to zero, i.e., for the suboptimal algorithm

$$\begin{cases} \dot{\rho}_j^{(i)} = \delta_j W_j \mathrm{sign}\left\{\sigma_j^{(i)}(t) - 0.5\sigma_{jM}^{(i)}\right\}, & j \neq 1 \\ \rho_j^{(i)} = 0, \quad j = i, \quad z_1(t) = 0 \\ \sigma^{(i)}(t) = \dot{e}^{(i)} + \beta e^{(i)} \end{cases} \tag{16}$$

and for the supertwisting algorithm

$$\begin{cases} z_{1j}^{(i)}(t) = & \lambda_j \sqrt{\left|\sigma_j^{(i)}(t)\right|} \mathrm{sign}\left(\sigma_j^{(i)}(t)\right), \quad j \neq i \\ \rho_j^{(i)}(t) = & \alpha_j \mathrm{sign}\left(\sigma^{(i)}(t)\right), \quad j \neq i \\ \rho_j^{(i)} = & 0, \quad z_{1j}^{(i)}(t) = 0, \quad j = i \\ \sigma^{(i)}(t) = & \dot{e}^{(i)} + \beta e^{(i)} \end{cases} \tag{17}$$

TABLE I
Signature Table for Sensor-Fault Isolation

Sen. 1 fault $r_{q1} = 1$	Sen. 2 fault $r_{q2} = 1$	... ...	Sen. n fault $r_{qn} = 1$
$\rho^{(1)} = 0$	$\rho^{(1)} \neq 0$	...	$\rho^{(1)} \neq 0$
$\rho^{(2)} \neq 0$	$\rho^{(2)} = 0$	...	$\rho^{(2)} \neq 0$
$\vdots$	$\vdots$	$\vdots$	$\vdots$
$\rho^{(n)} \neq 0$	$\rho^{(n)} \neq 0$	...	$\rho^{(n)} = 0$

with j as the index of the component of the state vector coinciding with the sensor number, while λ_j, α_j, $\sigma_{jM}^{(i)}$, and $\beta > 0$ are analogous to that defined for the actuators.

Note that, with this input law, the observer (15) has the ith component in open loop. This can imply stability problems also in the absence of faults, if the system is not open-loop stable by itself. To circumvent stability problems while avoiding a significant reduction of the detection performances, in the experimental tests, a local small-gain proportional-derivative feedback is closed to generate the ith input-law component of the ith observer (16). That is,

$$\rho_i^{(i)}(t) = K_p\left(q_i + \Delta q_i - \hat{\chi}_{1,i}^{(i)}\right) + K_d\left(-\hat{\chi}_{2,i}^{(i)}\right) \tag{18}$$

for all i, with $K_p > 0$ and $K_d > 0$ small constants.

More precisely, if $\hat{f}(\cdot)$ can be assumed to be a quite accurate estimate of $f(\cdot)$, a fault can be detected considering Table I. If, in contrast, $\hat{f}(\cdot)$ differs from $f(\cdot)$, thresholds need to be introduced. The entries of Table I expressed as $\rho^{(i)} \neq 0$ can be replaced by the condition

$$\text{if } \exists\, k \text{ s.t. } \left[\mathrm{sign}\left\{\rho^{(i)}\right\} \odot \rho^{(i)}\right]_k > T_k \tag{19}$$

while the entries of Table I expressed as $\rho^{(i)} = 0$ become

$$\left[\mathrm{sign}\left\{\rho^{(i)}\right\} \odot \rho^{(i)}\right]_k < T_k \qquad \forall k = 1, \ldots, n \tag{20}$$

where sign $\{\rho^{(i)}\}$ is the vector containing the sign of each component of $\rho^{(i)}$, the symbol $\odot$ denotes the Schur product, $[\cdot]_k$ denotes the kth component of a vector, and T_k is a positive real number representing the selected threshold.

A. FD Logic: Residual Generation and Fault Isolation

Fig. 1 shows the complete diagnostic scheme for robot manipulators. The residual vector r_τ is given by

$$r_{\tau i} = \begin{cases} 0 & \text{if } |\mathcal{F}(t) * \rho_i^\tau| < T_i^\tau \\ 1 & \text{if } |\mathcal{F}(t) * \rho_i^\tau| < T_i^\tau \end{cases} \qquad \forall i \tag{21}$$

while the residual vector r_q is obtained by filtering the $\rho_{j \neq i}^{(i)}(t)$ signals through the filter (12) and comparing these signals with their thresholds T_k, according to Table I.

The isolation of a fault can be performed by comparing the binary detection vector $[r_\tau, r_q]$ with the fault-signature Table II.

TABLE II
FAULT-SIGNATURE TABLE

Fault	$r_{\tau 1}$	$r_{\tau 2}$	$r_{\tau\, n}$	r_{q1}	r_{q2}	$r_{q\, n}$
None	0	0	0	0	0	0
Act. 1	1	0	0	p	p	p
Act. 2	0	1	0	p	p	p
Act. n	0	0	1	p	p	p
Sen. 1	p	p	p	1	0	0
Sen. 2	p	p	p	0	1	0
Sen. n	p	p	p	0	0	1

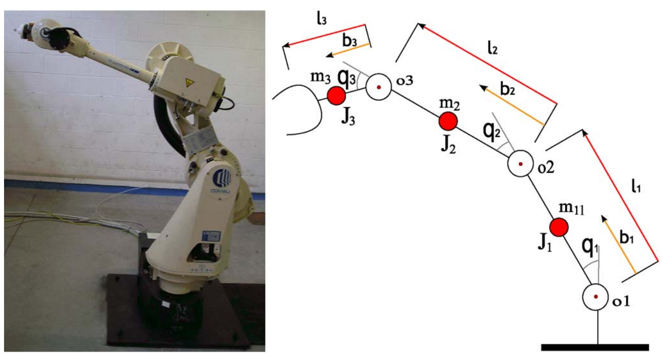

Fig. 3. SMART3-S2 robot and the three-link planar manipulator.

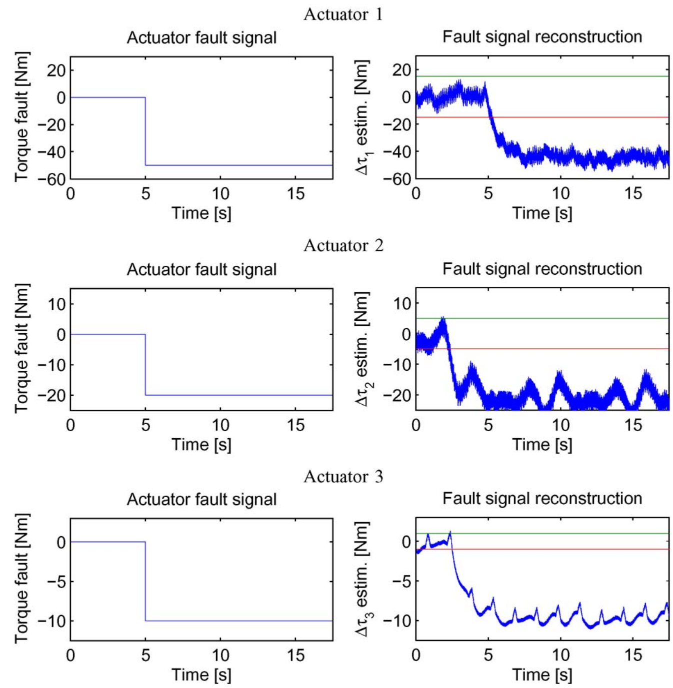

Fig. 4. FD experiment ($\Delta\tau$, $\widehat{\Delta\tau}$ signals). Supertwisting.

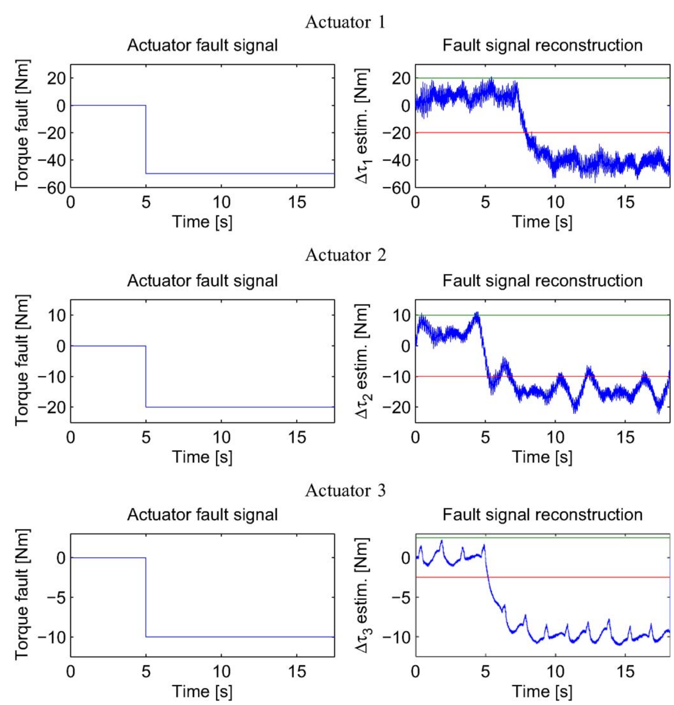

Fig. 5. FD experiment ($\Delta\tau$, $\widehat{\Delta\tau}$ signals). Suboptimal.

VI. CASE STUDY

A. Considered Manipulator

The FD 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. 3). It consists of six links and six rotational joints driven by brushless electric motors. 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. 3). Nevertheless, the method proposed in this paper holds for n-joint robots even of spatial type.

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

B. Experimental Tests

The faults are introduced in the control system by adding a fault signal to the 3-D control variable or to the 3-D measured displacements for the sensor faults.

The parameters for the suboptimal algorithm, chosen according to the parameter-selection rules indicated in [25], are $U_M = [362, 607, 10286]^{\mathrm{T}}$, with $\beta = 10$, while the parameter choice for the supertwisting is given by $\lambda = [7, 4, 17]^{\mathrm{T}}$ and $\alpha = [1.6, 2.0, 2.4]^{\mathrm{T}}$ according to [21, eq. (7)].

C. Experimental FD on Actuators

The case of abrupt faults on the actuators of each joint is considered, i.e., a $-50[\mathrm{N} \cdot \mathrm{m}]$ fault signal acting on the first actuator, a -20 $[\mathrm{N} \cdot \mathrm{m}]$ fault signal acting on the second actuator, and a -10 $[\mathrm{N} \cdot \mathrm{m}]$ fault signal acting on the third actuator are considered. Note that these fault signals are approximately the 20% of the maximum torque allowed by the corresponding actuator. In Fig. 4 for the supertwisting UIOs and in Fig. 5 for the suboptimal UIOs, the fault signals are correctly detected, isolated, and identified. The supertwisting approach, as for the fault that occurred on the first and second actuators, provides better performances, while as for the fault that occurred on the third actuator, the suboptimal approach shows a superior capability to avoid false alarms. Note that, theoretically, suboptimal

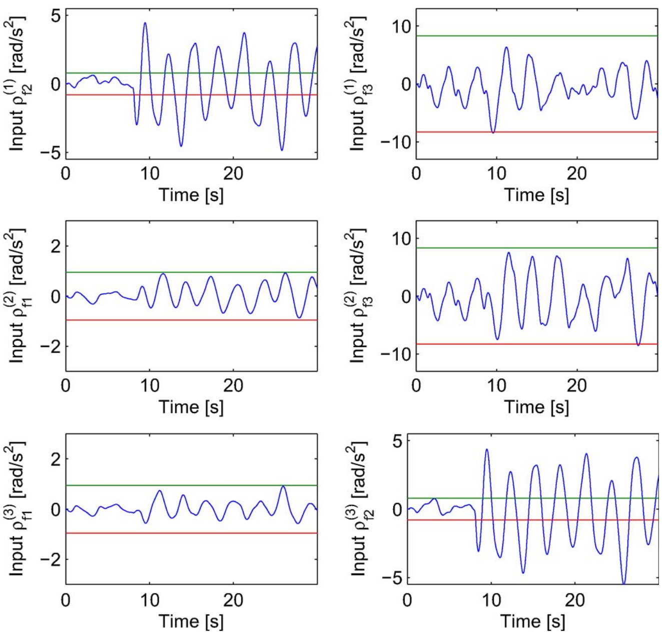

Fig. 6. Sensor 2 FD experiments: Suboptimal input law.

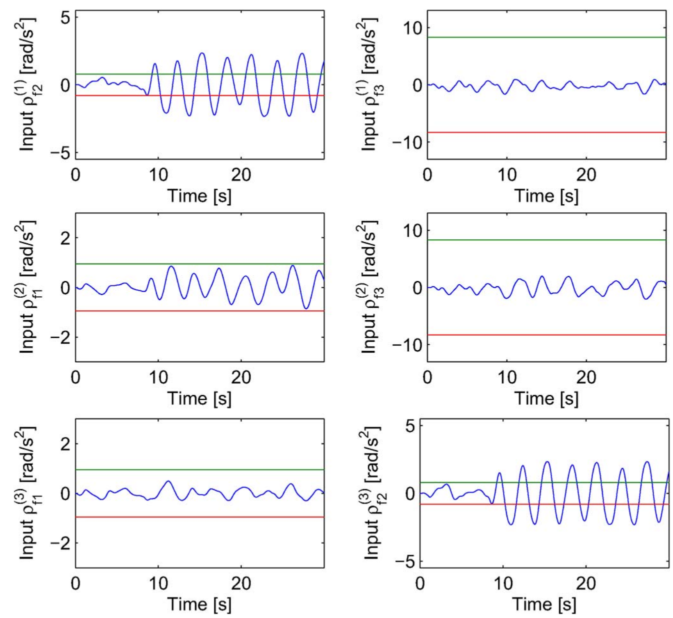

Fig. 7. Sensor 2 FD experiments: supertwisting input law.

and supertwisting differentiators have the same performance and this is confirmed by our experiments. The difference stands in the fact that for realizing the differentiation process using the suboptimal algorithm, a peak detector is required limiting the maximum value of the incoming signal. Supertwisting differentiator requires only the input signal. In turn, this can require the same filtering of the input. As a consequence, we have seen that one can use lower thresholds for the supertwisting, making the detection more precise, and higher thresholds for the suboptimal, reducing the false-alarm rate.

D. Experimental FD on Sensors

In the case of faults occurring on the sensors, the fault signature given in Table I is considered. The plots of Figs. 6 and 7 show the two components different from the zero of the input laws of the three GOS observers. Fig. 6 shows the results obtained by applying the suboptimal approach, while Fig. 7 reports the results obtained by applying the supertwisting approach. The fault has occurred on sensor 2. Both approaches can detect and isolate the fault, but they have different performances in terms of the possibility of making a reliable detection: The suboptimal strategy has produced a more clear response than that obtained with the supertwisting strategy.

E. Numerical Comparison of the Experimental Results

In order to compare the performance of the two observer approaches, the signals $\widehat{\Delta\tau}(t)$ and $\rho^{(i)}(t)$ have been evaluated in the case of actuator and sensor faults. Let t_f be the time instant in which the fault occurs. The sensitivity of the proposed approach to a fault occurring on the actuator j is evaluated as

$$FS\left(\widehat{\Delta\tau}_j(t)\right) = \max_{t>t_f}\left|\widehat{\Delta\tau}_j(t)\right| - \max_{0<t<t_f}\left|\widehat{\Delta\tau}_j(t)\right| \quad (22)$$

TABLE III
SENSITIVITY OF THE ACTUATOR FD STRATEGY

Signal	Sub-Optimal	Super-Twisting
$FS\left(\widehat{\Delta\tau}_1(t)\right)$	55-18=37[Nm]	58-20=38[Nm]
$FS\left(\widehat{\Delta\tau}_2(t)\right)$	25-7=18[Nm]	23-11=12[Nm]
$FS\left(\widehat{\Delta\tau}_3(t)\right)$	11-2=9[Nm]	11-3=8[Nm]

while the sensitivity of the proposed approach to a fault occurring on the sensor j is evaluated as

$$FS\left(\rho_j^{(i)}(t)\right) = \max_{t>t_f}\left|\rho_j^{(i)}(t)\right| - \max_{0<t<t_f}\left|\rho_j^{(i)}(t)\right|. \quad (23)$$

The positive values of $F_S(\cdot)$ indicate that the fault has been detected by the proposed approach, while null or the negative values of $F_S(\cdot)$ denote that the fault cannot be detected by relying on the proposed approach. According to the properties of the proposed modified GOS to detect sensor faults, a single fault occurring on the jth sensor can be correctly isolated only if it produces significant effects on the observers (i), $i \neq j$, but not on the observer (i), $i = j$. To evaluate this property, when a fault occurs on sensor i, the tolerance of the (i)th GOS observer to the fault occurring on sensor i is given as

$$FT_{ij}\left(\rho_j^{(i)}(t)\right) = \max_{t>t_f}\left|\rho_j^{(i)}(t)\right| j \neq i. \quad (24)$$

The lower values of $FT_{ij}(\cdot)$ indicate a better tolerance of the observer (j) versus a fault occurring on sensor i. In Tables III–V, the values of $FS(\widehat{\Delta\tau}_j(t))$ and $FS(\rho_i^{(i)}(t))$ have been shown in different situations. Table III reports the values of $FS(\widehat{\Delta\tau}_j(t))$ which have been evaluated in the case of three nonsimultaneous actuator faults $\Delta\tau(t)$, one for each component of the input signal $\tau(t)$. The first column reports the

TABLE IV
SENSITIVITY OF THE SENSOR FD STRATEGY IN [RADIANS PER SECOND SQUARED]. SUBOPTIMAL ALGORITHM IS ADOPTED

First experiment: $\Delta q_1 = 8,\ \Delta q_2 = \Delta q_3 = 0$(deg)

	Obs. (1)	Obs. (2)	Obs. (3)
$FS\left(\rho_1^{(i)}(t)\right)$	=	2.06-0.28=1.78	2.06-0.24=1.82
$FS\left(\rho_2^{(i)}(t)\right)$	2.40-0.72=1.68	=	0.33-0.54=-0.21
$FS\left(\rho_3^{(i)}(t)\right)$	4.90-5.00=-0.10	4.54-5.18=-0.64	=

Second experiment: $\Delta q_2 = -12,\ \Delta q_1 = \Delta q_3 = 0$(deg)

	Obs. (1)	Obs. (2)	Obs. (3)
$FS\left(\rho_1^{(i)}(t)\right)$	=	0.92-0.32=0.60	0.90-0.28=0.62
$FS\left(\rho_2^{(i)}(t)\right)$	5.20-0.80=4.40	=	5.41-0.70=4.71
$FS\left(\rho_3^{(i)}(t)\right)$	8.50-4.06=4.44	7.54-4.30=3.24	=

Third experiment: $\Delta q_3 = 11,\ \Delta q_1 = \Delta q_2 = 0$(deg)

	Obs. (1)	Obs. (2)	Obs. (3)
$FS\left(\rho_1^{(i)}(t)\right)$	=	0.28-0.18=0.10	0.23-0.18=0.05
$FS\left(\rho_2^{(i)}(t)\right)$	0.88-0.64=0.24	=	0.78-0.77=0.01
$FS\left(\rho_3^{(i)}(t)\right)$	11.50-3.28=8.22	10.95-3.30=7.65	=

TABLE V
SENSITIVITY OF THE SENSOR FD [RADIANS PER SECOND SQUARED]. SUPERTWISTING ALGORITHM

First experiment: $\Delta q_1 = 8,\ \Delta q_2 = \Delta q_3 = 0$(deg)

	Obs. (1)	Obs. (2)	Obs. (3)
$FS\left(\rho_1^{(i)}(t)\right)$	=	1.20-0.25=0.95	1.19-0.22=0.97
$FS\left(\rho_2^{(i)}(t)\right)$	1.55-0.60=0.95	=	1.00-0.52=0.48
$FS\left(\rho_3^{(i)}(t)\right)$	1.15-1.8=-0.65	1.83-1.54=0.29	=

Second experiment: $\Delta q_2 = -12,\ \Delta q_1 = \Delta q_3 = 0$(deg)

	Obs. (1)	Obs. (2)	Obs. (3)
$FS\left(\rho_1^{(i)}(t)\right)$	=	0.90-0.28=0.62	0.50-0.25=0.25
$FS\left(\rho_2^{(i)}(t)\right)$	2.35-0.70=1.65	=	2.35-0.6=1.75
$FS\left(\rho_3^{(i)}(t)\right)$	1.66-1.28=0.38	2.00-1.31=0.69	=

Third experiment: $\Delta q_3 = 11,\ \Delta q_1 = \Delta q_2 = 0$(deg)

	Obs. (1)	Obs. (2)	Obs. (3)
$FS\left(\rho_1^{(i)}(t)\right)$	=	0.20-0.16=0.04	0.21-0.17=0.04
$FS\left(\rho_2^{(i)}(t)\right)$	0.73-0.54=0.19	=	0.67-0.68=-0.01
$FS\left(\rho_3^{(i)}(t)\right)$	1.80-1.12=0.68	1.81-1.03=0.78	=

results obtained with the suboptimal, and the second column reports the results obtained with the supertwisting approach. In Tables IV and V, the same evaluation is made in the case of sensor faults. Three different experiments have been made. For each experiment, a single nonsimultaneous fault has been injected on a particular sensor. In Table IV are the reported values of $FS(\rho_i^{(i)}(t))$ using suboptimal, while Table V reports the same values obtained using supertwisting. The values of $FT_{ij}(\rho_j^{(i)}(t))$ are also reported in these two tables (see the first value of each cell, in the column referred to the observer associated to the faulty sensor).

From the numerical comparison shown in the tables, the suboptimal algorithm showed higher sensitivity values with respect to the supertwisting algorithm. In contrast, better performances in terms of tolerance have been obtained by considering the supertwisting approach, as the values relative to $FT_{ij}(\cdot)$ shown in Table V are smaller in all cases with respect to those obtained by applying the suboptimal approach.

VII. CONCLUSION

An FD scheme for robot manipulators based on the concept of SOSMs has been presented in this paper. The scheme presented in this paper allows to deal with the following cases: faults (even multiple) occurring only on the actuators and single faults occurring on actuators or sensors. The detection of the faults' presence on actuators is performed relying on UIOs, while the detection of the faults' presence on sensors is performed relying on a modified GOS. The observer input laws are designed according to two SOSM methodologies: the suboptimal approach and the supertwisting approach. The proposed FD approach can be extended also to some parametric faults (nonadditive). Future work will be devoted to deal with this topic. Experimental results on a real COMAU SMART3-S2 are presented. The numerical comparison showed that the proposed approach, when suboptimal algorithm is adopted for the input laws, has good sensitivity in the detection both for the actuators and for the sensors. In contrast, when the supertwisting approach is adopted for the observers involved in the GOS, it is possible to obtain better tolerance properties.

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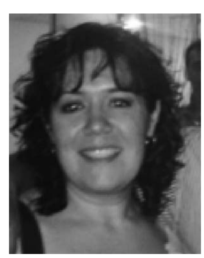

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