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An Adapt-and-Detect Actuator FDI Scheme for Robot Manipulators

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***Abstract*— An adaptive scheme is presented for actuator fault detection and isolation (FDI) in robotic systems, based on the use of generalized momenta and of a suitable overparametrization of the uncertain robot dynamics. This allows to obtain an accurate and reliable detection and isolation of possibly concurrent faults also during the parameter adaptation phase. Experimental results are reported for a planar robot under gravity, considering partial, total, or bias-type failures of the motor torques.**

***Index Terms*— Fault detection and isolation, robot actuator faults, nonlinear observers, adaptive schemes.**

I. Introduction

Fault detection and isolation (FDI) consists in recognizing the occurrence of a fault (detection) affecting the nominal behavior of a dynamic system, and discriminating it from other possible faults or disturbances (isolation). Instead of replicating critical components subject to fault (physical redundancy), a fault-tolerant behavior may be achieved also through the suitable processing of the available information (analytical redundancy) which would then trigger the task or control reconfiguration in response to the specific fault detected.

In the case of robot manipulators, any difference between the commanded torques and the actual driving torques experienced by the robot can be seen as an actuator fault. In this way, beside the partial or total failure of a motor, one can also model the occurrence of unexpected contacts with the environment or of motor saturation phenomena. FDI methods usually work with input-output signals and/or are based on the use of a dynamic model of the system. The most effective model-based approaches to robot actuators FDI imply a perfect decoupling property: for each input channel (joint torque subject to faults), an output signal (residual) is generated which, at least in nominal conditions, is affected only by faults occurring on that channel and is independent from other possible faults on different channels. Such a FDI scheme has been proposed in [1], based on a stable filtering of input torques and robot dynamics. In [2], the explicit use of generalized momenta led to the same result, but with a reduced computational load. Both schemes do not require joint acceleration measurements nor the simulation in parallel of the full robot dynamics.

In the presence of parametric uncertainties in the robot dynamic model, adaptive versions of FDI schemes should be devised. Furthermore, additional disturbances (measurement noises, unmodeled dynamics) require the use of small but finite detection thresholds in actual experiments; to increase sensitivity, the threshold values should be varied along with parameter adaptation. In [1], an adaptive FDI scheme has been proposed, based on the property of linearity in the unknown parameters of the robot dynamics. However, it is assumed that adaptation is done before the occurrence of any fault and, in addition, a new adaptation phase is needed at every change of the robot task trajectory.

The purpose of this paper is twofold: *i)* to present the actual implementation of the FDI scheme introduced in [2], including an adaptive version; *ii)* to propose and evaluate an over-

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parametrization of adaptive FDI schemes that allows to overcome, at least to some extent, the limitation of keeping separate adaptation and fault detection phases. Experimental results of this adapt-and-detect scheme are reported for the Quanser Pendubot, a $2R$ robot with a passive joint moving in the vertical plane, subject to intermittent and concurrent actuator torque faults.

II. Modeling

The dynamic model of a rigid robot manipulator, with generalized coordinates $q \in I\!R^n$, possibly undergoing actuator faults is

$$M(q)\ddot{q} + c(q,\dot{q}) + g(q) + F_v\dot{q} + F_c\text{sign}(\dot{q}) = u - u_f, \quad (1)$$

where $M(q) > 0$ is the (symmetric) inertia matrix, $c(q,\dot{q})$ is the Coriolis and centrifugal vector, $g(q)$ is the gravity vector, $F_v \geq 0$ and $F_c \geq 0$ are, respectively, the viscous and Coulomb friction (diagonal) matrices, u are the commanded (nominal) torques, and u_f are the (unknown) fault torques.

Note that eq. (1) captures any type of actuator fault, e.g., total or partial failure, bias, and saturation (see [2] for a complete list).

III. Actuator FDI Scheme

In [2], we have proposed a method for detecting and isolating actuator faults in robotic systems modeled by eq. (1), based on the use of the generalized momenta $p = M(q)\dot{q}$. In fact, one can write the following first-order dynamic equation

$$\dot{p} = u - u_f - \alpha(q,\dot{q}), \quad (2)$$

where the components of $\alpha(q,\dot{q})$, for $i = 1,\ldots,n$, are given by

$$\alpha_i = -\frac{1}{2}\dot{q}^T\frac{\partial M(q)}{\partial q_i}\dot{q} + g_i(q) + F_{vi}\dot{q}_i + F_{ci}\text{sign}(\dot{q}_i). \quad (3)$$

Note that only part of the Coriolis and centrifugal terms in c are present in α. From eq. (2), each fault (and nominal input torque) affects one and only one component of p. In particular, this decoupling allows identifying separately concurrent actuator faults, by defining the residual vector as

$$r = K\left[\int(u - \alpha - r)dt - p\right], \quad (4)$$

with $K = \text{diag}\{K_i\} > 0$ and $r(0) = 0$. The evaluation of r requires $(q,\dot{q})$ and the nominal input u but no acceleration $\ddot{q}$ nor inversion of the inertia matrix.

The residual dynamics satisfies

$$\dot{r}_i = -K_i r_i + K_i u_{f,i}, \quad i = 1,\ldots,n \quad (5)$$

namely that of *decoupled linear exponentially stable* systems driven by the faults $u_{f,i}$. The obtained result is similar to the FDI scheme proposed in [1], but requires less computations (the integral of α instead of filtering the whole left-hand side of eq. (1)). Moreover, the idea of using generalized momenta for designing an input FDI scheme is rather natural and can be extended to other electro-mechanical robotic systems (see [2]).

IV. Adapting the FDI Scheme

It is well known that the left-hand side of eq. (1) is a linear function of a suitably defined vector of constant dynamic parameters (see, e.g., [3]). Similarly, also the generalized momenta p and the nonlinear terms α in eq. (2) can be written as

$$p = Y_p(q,\dot{q})\theta_p, \quad \alpha = Y_\alpha(q,\dot{q})\theta_\alpha,$$

where θ_p and θ_α are separate parametrizations. From eqs. (1) and (2), it follows

$$Y(q,\dot{q},\ddot{q})\theta = \dot{Y}_p(q,\dot{q})\theta_p + Y_\alpha(q,\dot{q})\theta_\alpha = u - u_f. \quad (6)$$

In the presence of parametric uncertainty, p and α in eq. (4) should be replaced by their estimates

$$\hat{p} = Y_p(q,\dot{q})\hat{\theta}_p, \quad \hat{\alpha} = Y_\alpha(q,\dot{q})\hat{\theta}_\alpha,$$

so that eq. (4) is implemented as

$$r = K\left[\int\Big(u - Y_\alpha(q,\dot{q})\hat{\theta}_\alpha - r\Big)dt - Y_p(q,\dot{q})\hat{\theta}_p\right]. \quad (7)$$

In the absence of faults, the evolution of the residual vector r is driven by the uncertainty in the robot dynamic parameters knowledge

$$\dot{r} = -Kr - KY_\alpha\tilde{\theta}_\alpha - K\dot{Y}_p\tilde{\theta}_p - KY_p\dot{\hat{\theta}}_p, \quad (8)$$

being $\tilde{\theta}_\alpha = \hat{\theta}_\alpha - \theta_\alpha$ and $\tilde{\theta}_p = \hat{\theta}_p - \theta_p$ the parameter errors. Define the following adaptation rules

$$\dot{\hat{\theta}}_\alpha = \Gamma_\alpha Y_\alpha^T K r, \quad (9)$$

$$\dot{\hat{\theta}}_p = \Gamma_p \dot{Y}_p^T K r, \quad (10)$$

with $\Gamma_\alpha > 0$ and $\Gamma_p > 0$ (typically diagonal). In order to show that, in the absence of faults, the residual vector r asymptotically converges to zero, the following assumption is introduced.

Assumption 1: The robot joint position $q(t)$ and velocity $\dot{q}(t)$, the control input $u(t)$, and thus the acceleration $\ddot{q}(t)$, are $\mathcal{L}_\infty$ smooth functions.

Consider the following Lyapunov function for system (8–10)

$$V = \frac{1}{2} r^T r + \frac{1}{2} \tilde{\theta}_\alpha^T \Gamma_\alpha^{-1} \tilde{\theta}_\alpha + \frac{1}{2} \tilde{\theta}_p^T \Gamma_p^{-1} \tilde{\theta}_p \geq 0, \quad (11)$$

with $V = 0$ if and only if $r = \tilde{\theta}_\alpha = \tilde{\theta}_p = 0$. Since $\dot{\tilde{\theta}}_\alpha = \dot{\hat{\theta}}_\alpha, \dot{\tilde{\theta}}_p = \dot{\hat{\theta}}_p$, one has

$$\dot{V} = -r^T K (I + Y_p \Gamma_p \dot{Y}_p^T) r.$$

Under Assumption 1, $Y_p(t)$ and $\dot{Y}_p(t)$ are bounded, so that $\dot{V} \leq 0$ for a sufficiently small Γ_p. The asymptotic convergence of r to zero follows from the use of Barbalat's Lemma [4, p. 187], while nothing can be said in general for $\hat{\theta}_\alpha$ and $\hat{\theta}_p$ except that their steady-state values satisfy

$$Y_\alpha(q, \dot{q}) \tilde{\theta}_\alpha + \dot{Y}_p(q, \dot{q}) \tilde{\theta}_p = 0.$$

The computation of $\dot{Y}_p$ in eq. (10) would require joint acceleration measures. To avoid this, the update law (10) is modified by replacing $\dot{Y}_p$ with a finite difference approximation, i.e.,

$$\dot{\hat{\theta}}_p(t) = \Gamma_p \frac{Y_p^T(t) - Y_p^T(t-T)}{T} K r(t), \quad (12)$$

for a suitably chosen time $T > 0$.

The modified update law (12), for sufficiently small T, still guarantees the convergence of r to zero in the absence of faults ($u_f = 0$). To show this, the arguments used are more technical. The dynamics of the residual generator (8) and of the parameter adaptation (9–10) is that of an autonomous, linear, time-varying system with state $x = (r, \tilde{\theta}_\alpha, \tilde{\theta}_p)$, output $r = [I \ 0 \ 0]\, x = \mathcal{C} x$, and state matrix

$$\mathcal{A}(t) = \begin{bmatrix} -K' & -K Y_\alpha(t) & -K \dot{Y}_p(t) \\ \Gamma_\alpha Y_\alpha^T(t) K & 0 & 0 \\ \Gamma_p \dot{Y}_p^T(t) K & 0 & 0 \end{bmatrix},$$

where $K' = K(I + Y_p \Gamma_p \dot{Y}_p^T)$. By the Lyapunov argument used to show the convergence of r to zero, it follows that, at any 'frozen' time $t = \bar{t}$, the quotient system corresponding to the observable part of $(\mathcal{A}(\bar{t}), \mathcal{C})$ has eigenvalues with negative real part. Since the chosen Lyapunov function (11) is time-invariant, this quotient system is 'slowly varying' (in the sense of [4, p. 278]). By continuity arguments, the properties of having eigenvalues with negative real part at all times and being slowly varying are inherited also by a perturbed system with state matrix $\mathcal{A}^*(t)$ sufficiently close to $\mathcal{A}(t)$. In the present case, this holds true for

$$\mathcal{A}^*(t) = \begin{bmatrix} -K'' & -K Y_\alpha(t) & -K \dot{Y}_p(t) \\ \Gamma_\alpha Y_\alpha^T(t) K & 0 & 0 \\ \Gamma_p \frac{Y_p^T(t) - Y_p^T(t-T)}{T} K & 0 & 0 \end{bmatrix},$$

where $K'' = K(I + Y_p \Gamma_p \frac{Y_p^T(t) - Y_p^T(t-T)}{T})$, provided that T is sufficiently small. Therefore, since a linear, slowly-varying system having eigenvalues with negative real part at all times is asymptotically stable, convergence of r to zero with the modified adaptation scheme (9,12) follows.

V. An Adapt-and-Detect Scheme

Following [1], in order to make the proposed FDI scheme adaptive, one may perform a preliminary parameter tuning, during which the residual vector is driven below a dynamically set threshold, and then stop adaptation, having the FDI system ready to detect possible actuator faults. However, such an approach suffers from some limitations:

- The FDI functionality of the system is disabled during parameter adaptation.
- The steady-state values of the parameter estimates ($\hat{\theta}$ or $(\hat{\theta}_\alpha, \hat{\theta}_p)$) depend on the robot task trajectory. In general, a new adaptation phase must be performed each time the class of trajectories changes.
- The threshold for fault detection depends on the value attained by the residual r when the adaptation phase is stopped. The higher is the desired detection sensitivity, the longer must be the adaptation phase.

In order to overcome these limitations, an overparametrization of the robot dynamics can be considered. For $i = 1, \ldots, n$, rewrite the i-th equation in (2) as

$$\dot{Y}_{p,i}(q,\dot{q})\theta_p^i + Y_{\alpha,i}(q,\dot{q})\theta_\alpha^i = u_i - u_{f,i}, \qquad (13)$$

where $Y_{p,i}(q,\dot{q})$ and $Y_{\alpha,i}(q,\dot{q})$ are, respectively, the i-th row[1] of $Y_p(q,\dot{q})$ and of $Y_\alpha(q,\dot{q})$. Different sets of dynamic parameters θ_p^i and θ_α^i have been introduced for each scalar equation describing the robot dynamics. Accordingly, the i-th component of the residual is defined as

$$r_i = K_i \left[\int \left(u_i - Y_{\alpha,i}(q,\dot{q})\hat{\theta}_\alpha^i - r_i \right) dt - Y_{p,i}(q,\dot{q})\hat{\theta}_p^i \right], \qquad (14)$$

with adaptation rules, for $i = 1, \ldots, n$,

$$\begin{aligned} \dot{\hat{\theta}}_\alpha^i(t) &= \Gamma_\alpha^i Y_{\alpha,i}^T(t) K_i r_i(t) \\ \dot{\hat{\theta}}_p^i(t) &= \Gamma_p^i \frac{Y_{p,i}^T(t) - Y_{p,i}^T(t-T)}{T} K_i r_i(t), \end{aligned} \qquad (15)$$

being Γ_α^i and Γ_p^i positive definite matrices.

The adaptive FDI scheme (14–15) has the same formal structure of (7), (9), and (12), sharing thus the same convergence properties. At the cost of a higher dimension of the parameter update dynamics, this modified scheme has the following properties:

- The residual components r_i, $i = 1, \ldots, n$, are completely decoupled also during the adaptation phase. A failure of the k-th actuator will raise r_k, triggering the adaptation of the parameter vectors θ_α^k and θ_p^k but not affecting the other residuals and parameter vectors r_i, θ_α^i, and θ_p^i, for $i \neq k$.
- At the occurrence of a failure on the k-th input channel, the dynamics of r_k will be driven by the input fault $u_{f,k}$ as well as by the parameter estimation errors $\tilde{\theta}_\alpha^k$, $\tilde{\theta}_p^k$. It will thus stay generically nonzero during the fault interval, despite of parameter adaptation.

Thus, detection of possible actuator faults while continuously adapting parameter estimates (e.g., in response to payload or friction changes) becomes feasible. In principle, faults can be detected and isolated as soon as the FDI system is started and, in particular, even before parameter adaptation has driven the residuals below the thresholds of desired detection accuracy.

[1]Only non-zero elements of the i-th row are used.

Note finally that θ_α^i and θ_p^i contain in general just a subset of the parameters θ_α and θ_p, i.e., only those appearing in the i-th robot dynamic equation. As a typical example, overparametrization of friction coefficients is not necessary since these parameters are already local to each joint.

VI. Experimental Results

The adaptive FDI scheme (14–15) has been tested on the Quanser Pendubot, a $2R$ planar robot under gravity whose first joint is driven by a DC motor and second joint is unactuated (see Fig. 1). The dynamic model (1) takes the form

$$\begin{bmatrix} a_1 + 2a_2c_2 & a_3 + a_2c_2 \\ a_3 + a_2c_2 & a_3 \end{bmatrix} \begin{bmatrix} \ddot{q}_1 \\ \ddot{q}_2 \end{bmatrix} + \begin{bmatrix} -a_2\dot{q}_2(\dot{q}_2 + 2\dot{q}_1)s_2 \\ a_2\dot{q}_1^2 s_2 \end{bmatrix} + \begin{bmatrix} a_4s_1 + a_5s_{12} \\ a_5s_{12} \end{bmatrix} + \begin{bmatrix} F_{v1}\dot{q}_1 \\ F_{v2}\dot{q}_2 \end{bmatrix} + \begin{bmatrix} F_{c1}\mathrm{sign}(\dot{q}_1) \\ F_{c2}\mathrm{sign}(\dot{q}_2) \end{bmatrix} = \begin{bmatrix} u_1 - u_{f1} \\ u_2 - u_{f2} \end{bmatrix},$$

where $(q_1, q_2) = 0$ is the downward equilibrium configuration and a shorthand notation is used for sine/cosine. Being the second joint passive, it is always $u_2 = u_{f2}$. The dynamic coefficients a_i ($i = 1, \ldots, 5$) are defined as in [3, p. 152], while F_{vi} and F_{ci} are, respectively, the viscous and Coulomb friction coefficients at the i-th joint. The vector α in eq. (2) is given by

$$\begin{aligned} \alpha_1 &= a_4s_1 + a_5s_{12} + F_{v1}\dot{q}_1 + F_{c1}\mathrm{sign}(\dot{q}_1) \\ \alpha_2 &= a_2\dot{q}_1(\dot{q}_1 + \dot{q}_2)s_2 + a_5s_{12} + F_{v2}\dot{q}_2 + F_{c2}\,\mathrm{sign}(\dot{q}_2). \end{aligned}$$

Moreover, $\theta_\alpha = (a_2, a_4, a_5, F_{v1}, F_{c1}, F_{v2}, F_{c2})$ and $\theta_p = (a_1, a_2, a_3)$ with associated

$$Y_\alpha = \begin{bmatrix} 0 & s_1 & s_{12} & \dot{q}_1 & \mathrm{sign}(\dot{q}_1) & 0 & 0 \\ s_2\dot{q}_1(\dot{q}_1 + \dot{q}_2) & 0 & s_{12} & 0 & 0 & \dot{q}_2 & \mathrm{sign}(\dot{q}_2) \end{bmatrix}$$

$$Y_p = \begin{bmatrix} \dot{q}_1 & c_2(2\dot{q}_1 + \dot{q}_2) & \dot{q}_2 \\ 0 & c_2\dot{q}_1 & \dot{q}_1 + \dot{q}_2 \end{bmatrix}.$$

The overparametrization leads in this case to

$$\theta_\alpha^1 = (a_4, a_5, F_{v1}, F_{c1}), \quad \theta_\alpha^2 = (a_2, a_5, F_{v2}, F_{c2})$$
$$\theta_p^1 = (a_1, a_2, a_3), \qquad \theta_p^2 = (a_2, a_3).$$

Joint positions are measured by sliding-contact encoders, which makes friction modeling harder, while velocities are obtained by numerical differentiation.

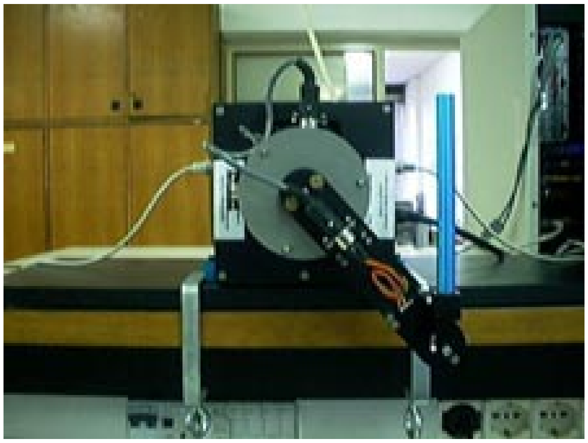

Fig. 1. The Quanser Pendubot

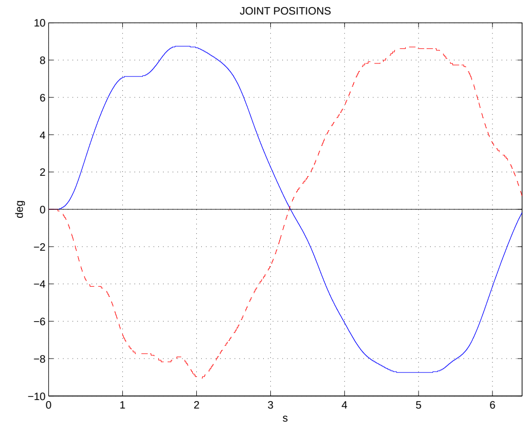

Fig. 2. Experiment 1 – Joint positions q_1 (blue, solid) and q_2 (red, dashed)

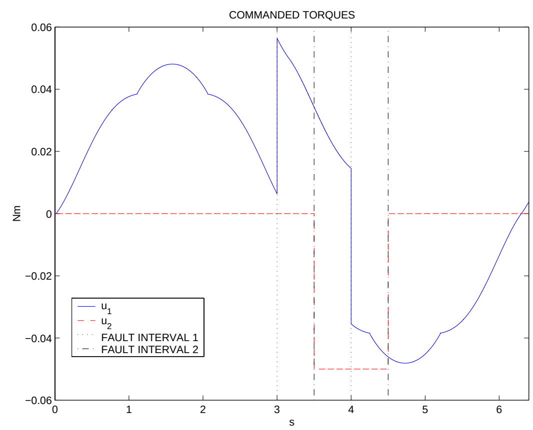

Fig. 3. Experiment 1 – Commanded torques u_1 (blue, solid) and u_2 (red, dashed)

Different types of faults have been tested on the first joint actuator, while on the second (unactuated) joint only a total actuator failure can be emulated (by nominally requiring some torque that, of course, cannot be provided). We report here the results of two experiments, the first in open-loop and the second under feedback control. The following values were used in eqs. (14–15): $K_i = 50$, $\Gamma_\alpha^i = \Gamma_p^i = 0.01$ $(i = 1, 2)$, and $T = 0.001$ s. The estimates of all dynamic parameters have been initialized to 90% of their real values[2]. The range of variation for each parameter estimate $\hat{\theta}_i(t)$ has been limited to $[0.5, 1.5]\,\hat{\theta}_i(0)$ (a maximum error of 50% has been assumed for the initial estimate $\hat{\theta}_i(0)$).

Experiment 1

The DC motor at the first joint is driven by an open-loop sinusoidal voltage of amplitude 0.1 V and angular frequency 1 rad/s. For $t \in [3, 4]$ s, the commanded torque is increased by a constant bias of 0.05 Nm, while the applied torque keeps the previous profile. A total failure of the second joint torque occurs for $t \in [3.5, 4.5]$ s (the commanded torque was -0.05 Nm). Thus, the two faults are concurrent for $t \in [3.5, 4]$ s. Figures 2–4 show the behavior of joint positions, commanded torques, and residual components. Fault time intervals are also indicated.

From Fig. 4, detection and isolation of the two actuator faults is clear. Note that both residuals have almost reached their steady-state values when faults occur, and asymptotically converge to zero at the end of the fault interval (the noisy behavior of residual r_1 is introduced by the PWM circuit driving the DC motor).

Experiment 2

The first joint variable is being regulated to the reference value $q_{1d} = 30°$ by a PID controller with gains $K_P = 0.2$, $K_I = 1$ and $K_D = 0.02$. A 50% loss of power ($u_{f,1} = 0.5u_1$) is experienced by the first actuator for $t \in [1.7, 2]$ s and a total failure of the second joint torque occurs for $t \in [1.9, 2.4]$ s

[2]Previously identified robot parameters values are used: $m_1 = 0.193$ and $m_2 = 0.073$ [kg]; $l_1 = 0.1492$, $d_1 = 0.1032$, and $d_2 = 0.084$ [m]; $I_1 = 0.0015$ and $I_2 = 1.949 \cdot 10^{-4}$ [kgm^2]. In the operating conditions of the experiments, the values of viscous and Coulomb friction coefficients are $(F_{v1}, F_{v2}) = (5.753, 0.28) \cdot 10^{-4}$ [Nms] and $(F_{c1}, F_{c2}) = (0.0052, 0.0001)$ [Nm].

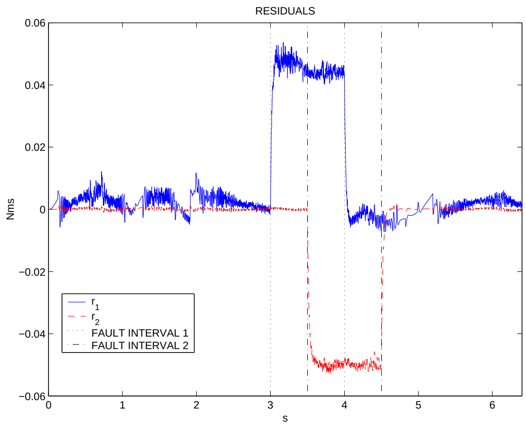

Fig. 4. Experiment 1 – Residuals r_1 (blue, solid) and r_2 (red, dashed)

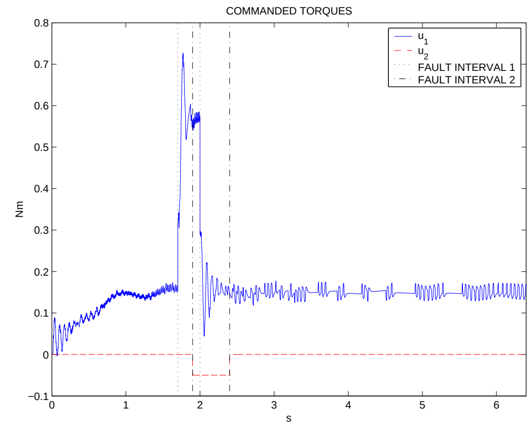

Fig. 6. Experiment 2 – Commanded torques u_1 (blue, solid) and u_2 (red, dashed)

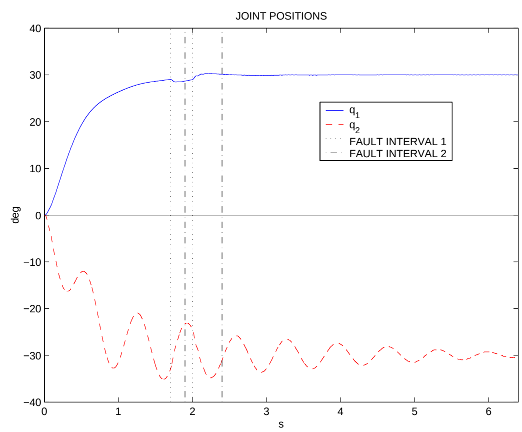

Fig. 5. Experiment 2 – Joint positions q_1 (blue, solid) and q_2 (red, dashed)

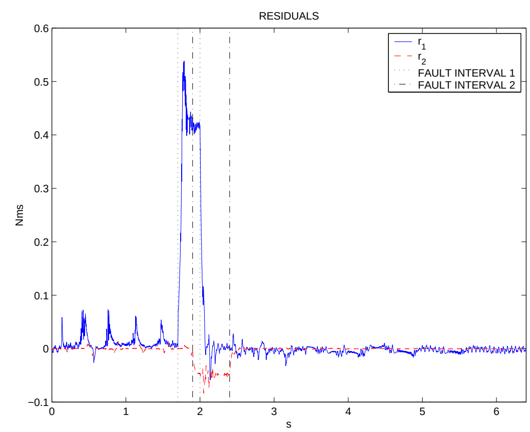

Fig. 7. Experiment 2 – Residuals r_1 (blue, solid) and r_2 (red, dashed)

(the commanded torque was -0.05 Nm). Again, fault concurrence is present for $t \in [1.9, 2]$ s. Figures 5–7 show the obtained results. In this case, the two faults occur at a very early stage of parameter adaptation. Nevertheless, both faults can be clearly detected and distinguished from the behavior of the two residuals in Fig. 7.

VII. Conclusions

A new adaptive scheme for detecting and isolating actuator faults in robot manipulators has been proposed and evaluated experimentally, based on the use of generalized momenta as introduced in [2]. The FDI scheme works under uncertain knowledge on the robot dynamic parameters and allows a more reliable fault detection even when dynamic parameters are still being adapted, thanks to a suitable overparametrization. The experimental results indicate that detection performance is suitable for real-time activation of control or task reconfiguration strategies in response to the isolated faults.

References

[1] W. Dixon, I. Walker, D. Dawson, and J. Hartranft, "Fault detection for robot manipulators with parametric uncertainty: A prediction-error-based approach," *IEEE Trans. on Robotics and Automation*, vol. 16, no. 6, pp. 689–699, 2000.

[2] A. De Luca and R. Mattone, "Actuator fault detection and isolation using generalized momenta," in *Proc. of 2003 IEEE Int. Conf. on Robotics and Automation*, pp. 634–639, 2003.

[3] L. Sciavicco and B. Siciliano, *Modeling and Control of Robot Manipulators.* London: Springer, 2nd Ed., 2000.

[4] H. Khalil, *Nonlinear Systems.* New York: Macmillan, 1992.