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Energetic Approach to Deal with Faults in Robot Actuators

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***Abstract*—In this paper it is investigated, how the energy monitoring of robotic systems can be applied for detection and isolation of robot actuator faults. Firstly, the relations describing the energy balance of a robot are recalled. Then it is showed how the actuator faults influence the energy balance of the robot. The deviation of the robot energy from its normal balance is used to detect the presence of fault in the robot actuator. For fault isolation the set of fault energy patterns is defined. The fault induced energy deviation is compared with the elements of the fault energy pattern set using standard signal processing methods. The problems of fault identification and multiple fault detection are also treated. Simulation results are provided to show the applicability of the proposed fault detection and isolation method.**

***Index Terms*—Fault detection, Fault diagnosis, Robot, Correlation, Energy balance**

I. Introduction

Most of the currently applied robotic manipulators work in such industrial environments in which the robots can perform their predefined task in a relatively safe manner. However there is an increasing demand for such robotic applications that have to be carried out in unknown environments and the robots may be exposed to hazards and faults. In such cases the reliability and fault tolerance of the robot control system is a key issue.

The faults can generate total failure (e.g. complete mechanical jamming) or partial failure (e.g. increased resistance in motion due to the partial loss of lubricant in gear transmission) of the robotic system. Total failures induce functional disorder and accordingly the machine has to be shut down. In the case of partial failures the machine may still remain in operation, but in order to preserve its original control performances, in many cases, the reconfiguration of the control law is necessary. The long term use of the machine with partial faults may also lead to total failure. It is why the timely detection of the partial failures is also an important problem and detectors for partial failure have to be implemented in the control systems of robots that work in hazardous environments.

The problem of detection and isolation of faults in robot control systems were in focus of the researchers starting from the first industrial applications of robot manipulators. A survey of the early results in this field can be found in the paper [1].

A substantial part of the currently introduced algorithms for fault detection in robot control systems are based on disturbance observers. A joint disturbance observer for robot manipulators was presented in [2] to estimate the reaction force due to component disinsertion for robot assembly tasks. Based on the dynamic nonlinear model of the robot such disturbance observers were proposed in [3] and [4] for fault detection, that do not require acceleration measurement or estimation. A nonlinear disturbance observer for 2 Degrees of Freedom robotic manipulators was proposed in [5]. Force and joint sensors based robot fault detection and isolation methods were proposed in [6] and [7].

Fault detection requires precise modeling of the manipulator and precise knowledge on the parameters of the dynamic model. It is why the friction in the joints of the manipulator should also be taken into consideration during modeling. There are several methods to model the friction in robot manipulators and to identify the frictional parameters, see [8] and the references therein. Moreover the increased friction in gear transmissions may lead to faults that deteriorate the performance of the robot control system. A neural network based fault detection scheme for mechanical systems with LuGre friction performing linear motions was proposed in [9]. In the paper [10] a fault detection algorithm was developed to isolate and detect friction changes in a high precision pneumatic positioning mechanism. The study [11] proposed a fault detection algorithm for a class of nonlinear systems that can be applied for the detection of increased friction in mechanical control systems.

Incipient faults are a special class of low magnitude faults, which have the characteristic that they are developing slowly in time. These faults can be detected using on-line parameter estimation techniques [12] or additional excitation signals have to be designed and applied to the system's input [13].

To detect low magnitude faults, the monitoring of the energy flow of the control system can also be applied. In the paper [14] an energy balance based fault detection scheme was proposed for a class of linear dissipative systems. In the work [15] fault detection and isolation method was proposed

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for port-Hamiltonian systems to detect parameter variations. The energy balance based fault detection was also applied for sensor fault detection in steel galvanizing process, see [16].

In this work an energy monitoring based fault detection and isolation method is developed for robotic systems. It is explored that the energy of Euler-Lagrange systems can be calculated based on its dynamic model. The fault induced energy will modify the energy balance of the robotic system; hence for fault detection the monitoring of the energy balance deflection of the robot is necessary. For the isolation and identification of the faults signal processing methods, such as the correlation operator, are applied. In order to detail the proposed method, the rest of this paper is organized as follows: Section II presents the dynamic model and the energy equations of robotic systems. The proposed fault detection identification and isolation method is introduced in Section III. Simulation results are presented in Section IV. Finally, Section V concludes this study.

II. The energy of robots

The dynamics of a n Degrees Of Freedom (DOF) manipulator is described by the following relation [17]:

$$H(\mathbf{q})\ddot{\mathbf{q}} + C(\mathbf{q},\dot{\mathbf{q}})\dot{\mathbf{q}} + \mathbf{G}(\mathbf{q}) = \tau - \tau_F(\dot{\mathbf{q}}), \tag{1}$$

where $\mathbf{q} \in \mathbf{R}^n$ denotes the joint position vector, the vector $\tau \in \mathbf{R}^n$ contains the control torques/forces developed by the joint actuators, $\tau_F \in \mathbf{R}^n$ is the vector of the friction generated torques/forces. The inertial matrix is $H(\mathbf{q}) \in \mathbf{R}^{n\times n}$, the vector $C(\mathbf{q},\dot{\mathbf{q}})\dot{\mathbf{q}} \in \mathbf{R}^n$ includes the effect of centrifugal and Coriolis forces. The notation $\mathbf{G}(\mathbf{q}) \in \mathbf{R}^n$ stands for the gravitational forces and gravity induced torques.

The model of the robot has the following properties:

- (P1) The inertia matrix is symmetric and positive definite: $H(\mathbf{q}) > 0,\ \forall \mathbf{q}$.
- (P2) The matrix $\dot{H}(\mathbf{q}) - 2C(\mathbf{q},\dot{\mathbf{q}})$ is skew symmetric: $\mathbf{x}^T\left(\dot{H}(\mathbf{q}) - 2C(\mathbf{q},\dot{\mathbf{q}})\right)\mathbf{x} = 0,\ \forall \mathbf{x} \in \mathbf{R}^n$.

The friction in the model can be described as a velocity dependent term. A widely used model to describe the friction phenomena in the joints of the robot is the Coulomb + viscous friction model. In the ith joint of the robot this friction model is given by:

$$\tau_{Fi}(\dot{q}_i) = F_{Ci}\,\mathrm{sgn}(\dot{q}_i) + F_{Vi}\dot{q}_i, \tag{2}$$

where F_{Ci} is the Coulomb friction parameter and F_{Vi} is the viscous friction parameter in the ith joint.

In this work it is assumed that $\mathbf{q}$ and $\dot{\mathbf{q}}$ are measurable and the parameters of the robot model are known.

Consider that the input of the system is the control torque τ and its output is the joint velocity vector $\dot{\mathbf{q}}$. The input-output behavior of the system can be analyzed in energetic approach.

The *total energy* of the robot can be written as a sum of its kinetic and potential energy:

$$E = K + P = \frac{1}{2}\dot{\mathbf{q}}^T H(\mathbf{q})\dot{\mathbf{q}} + P(\mathbf{q}). \tag{3}$$

The configuration dependent potential energy $P(\mathbf{q})$ is associated with gravitational effects. It is defined here relative to a level such that $P(\mathbf{q}) \geq 0$ for each configuration of the robot.

The evolution in time of the robot energy is given by:

$$\dot{E} = \dot{K} + \dot{P} = \dot{\mathbf{q}}^T H(\mathbf{q})\ddot{\mathbf{q}} + \frac{1}{2}\dot{\mathbf{q}}^T \dot{H}(\mathbf{q})\dot{\mathbf{q}} + \nabla P(\mathbf{q})^T\dot{\mathbf{q}}, \tag{4}$$

where ∇ is the gradient operator.

By introducing $H(\mathbf{q})\ddot{\mathbf{q}}$ from the relation (1) we obtain:

$$\begin{aligned}\dot{E} &= \dot{\mathbf{q}}^T\left(\tau - C(\mathbf{q},\dot{\mathbf{q}})\dot{\mathbf{q}} - \mathbf{G}(\mathbf{q}) - \tau_F(\dot{\mathbf{q}})\right) + \\ &+ \frac{1}{2}\dot{\mathbf{q}}^T\dot{H}(\mathbf{q})\dot{\mathbf{q}} + \nabla P(\mathbf{q})^T\dot{\mathbf{q}}.\end{aligned} \tag{5}$$

The conservative gravitational force is equal with the gradient of the gravitational potential energy, i.e. $\nabla P(\mathbf{q}) = \mathbf{G}(\mathbf{q})$. Moreover by applying the skew symmetric property (P2) we obtain:

$$\dot{E} = \dot{\mathbf{q}}^T\tau - \dot{\mathbf{q}}^T\tau_F(\dot{\mathbf{q}}). \tag{6}$$

Same result can be obtained by examining only the *kinetic energy* of the system:

$$K = \frac{1}{2}\dot{\mathbf{q}}^T H(\mathbf{q})\dot{\mathbf{q}}. \tag{7}$$

In this case the input of the mechanical system has to be reformulated as the difference between the control input torques and the gravitational term $\mathbf{G}(\mathbf{q})$. With similar argumentation as in the case of the total energy, the evolution in time of the kinetic energy is given by:

$$\dot{K} = \dot{\mathbf{q}}^T\left(\tau - \mathbf{G}(\mathbf{q})\right) - \dot{\mathbf{q}}^T\tau_F(\dot{\mathbf{q}}). \tag{8}$$

In the dissipative systems theory the scalar product of the input and output $\dot{\mathbf{q}}^T\left(\tau - \mathbf{G}(\mathbf{q})\right)$ defines the supply rate of the system.

Due to the dissipative nature of friction we have $\dot{\mathbf{q}}^T\tau_F(\dot{\mathbf{q}}) \geq 0$ (see e.g. the friction model given by (2)).

Accordingly $\dot{K} \leq \dot{\mathbf{q}}^T\left(\tau - \mathbf{G}(\mathbf{q})\right)$ and it can also be shown that the robotic system is passive [18].

The equations (8) and (6) are equivalent. The difference between the two formulations is given by the fact that the equation (8) depends explicitly on the gravitational forces while the equation (6) depends on the gravitational potential energy trough E.

The *energy balance of the robotic system* over a time period T can be written as:

$$K(t) - K(t-T) + \int_{t-T}^{t}\dot{\mathbf{q}}^T\tau_F(\dot{\mathbf{q}})d\xi = \int_{t-T}^{t}\dot{\mathbf{q}}^T\left(\tau - \mathbf{G}(\mathbf{q})\right)d\xi. \tag{9}$$

The terms of the energy balance are:

- $K(\cdot)$ - the stored kinetic energy of the mechanical system in a time instant.
- $\int_{t-T}^{t}\dot{\mathbf{q}}^T\tau_F(\dot{\mathbf{q}})d\xi$ - the energy dissipated by the friction.
- $\int_{t-T}^{t}\dot{\mathbf{q}}^T\left(\tau - \mathbf{G}(\mathbf{q})\right)d\xi$ - the difference between externally delivered energy by the joint actuators and by the gravity.

The energy balance of mechanical systems has been successfully applied for control design. Control algorithms can be developed to shape the energy of the control system, see for example the review paper [19].

III. ENERGETIC FAULT DETECTION, ISOLATION AND IDENTIFICATION

A. Detection algorithm

The robot actuators are exposed to various faults. The total failure of the actuator can manifest in free swinging joint (complete power loss) or locked joint (because of jamming of bearings or transmission, or failure of the motor in braked condition). Partial failure in robot control system may cause increased resistance in joint movement (e.g. due to loss of lubrication) or vibrations (e.g. due to increased backlash). In many cases these failures can be modeled as additive fault torques which appear in the robot model:

$$H(\mathbf{q})\ddot{\mathbf{q}} + C(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}} + \mathbf{G}(\mathbf{q}) = \tau - \tau_F(\dot{\mathbf{q}}) + \mathbf{f}, \qquad (10)$$

where $\mathbf{f} \in \mathbf{R}^n$ is the fault event generated torques/forces.

Below the most important fault torques/forces are enumerated. In the case of *increased motion resistance* in the ith joint the fault can be modeled as:

$$f_{i1} = -K_{Fi1}\,\mathrm{sgn}(\dot{q}_i),\;\; K_{Fi1} > 0. \qquad (11)$$

In the case of *loss of efficiency* the fault manifests as:

$$f_{i2} = -K_{Fi2}\tau_i,\;\; K_{Fi2} \in (0, 1]. \qquad (12)$$

In the case of complete power loss joint the magnitude parameter will take the value $K_{Fi2} = 1$.

The *locked joint* can be modeled as:

$$f_{i3} = -\tau_i + u(q_i, q_{iL}), \qquad (13)$$

where u defines a high gain control law which keeps the robot joint steady in the locked position q_{iL}.

A *vibration* can be modeled as a periodic signal s with a given angular frequency (ω_i):

$$f_{i4} = K_{Fi4}s(\omega_i t). \qquad (14)$$

The actuator fault modifies the energy balance of the mechanical system as well. A new energy term appears in the energy balance equation (9) as follows:

$$\begin{aligned} K(t) \;&-\; K(t-T) + \int_{t-T}^{t} \dot{\mathbf{q}}^T \tau_F(\dot{\mathbf{q}}) d\xi + \qquad (15) \\ &+\; \int_{t-T}^{t} \dot{\mathbf{q}}^T \left(-\tau + \mathbf{G}(\mathbf{q})\right) d\xi = \int_{t-T}^{t} \dot{\mathbf{q}}^T \mathbf{f} d\xi. \end{aligned}$$

Based on the relation above, with known robot parameters and measured joint position and velocity, the energy injected by the fault into the system can be calculated.

Accordingly the 'energetic' residual signal generator for fault detection can be formulated as:

$$\begin{aligned} r_E(t) \;&=\; K(t) - K(t-T) \qquad (16) \\ &+\; \int_{t-T}^{t} \dot{\mathbf{q}}^T \left(-\tau + \mathbf{G}(\mathbf{q}) + \tau_F(\dot{\mathbf{q}})\right) d\xi. \end{aligned}$$

The decision signal for fault detection is formulated as:

$$d_E = \begin{cases} 1, \text{ if } |r_E(t)| > th, \\ 0, \text{ otherwise.} \end{cases} \qquad (17)$$

Here $th > 0$ is a threshold value introduced to deal with modeling errors.

Sensitivity and robustness: The dominant part of the residual signal is the last integral term of the relation (16). Since the integrator suppresses the high frequency components of the power signals the residual generator has an intrinsic low pass filter characteristic; the detection will have low sensitivity on the high frequency disturbances (such as high frequency measurement errors). The filtering properties can be set with only one parameter which is the length of the energy observation period (T). For high T values the attenuation of the high frequency noises is more accentuated but the detector will have slower response time.

Now consider that the uncertainties of the robot model dependent terms of the energy balance can be written in additive form with given upper bounds.

$$\begin{aligned} H(\mathbf{q}) \;&=:\; H(\mathbf{q}) + \delta H(\mathbf{q}),\;\; |\sigma_M\left(\delta H(\mathbf{q})\right)| \le \Delta\sigma(\mathbf{q}), \\ \mathbf{G}(\mathbf{q}) \;&=:\; \mathbf{G}(\mathbf{q}) + \delta\mathbf{G}(\mathbf{q}),\;\; |\delta\mathbf{G}(\mathbf{q})| \le \Delta\mathbf{G}(\mathbf{q}), \qquad (18) \\ \tau_F(\dot{\mathbf{q}}) \;&=:\; \tau_F(\dot{\mathbf{q}}) + \delta\tau_F(\dot{\mathbf{q}}),\;\; |\delta\tau_F(\dot{\mathbf{q}})| \le \Delta\tau_F(\dot{\mathbf{q}}). \end{aligned}$$

$\sigma_M(\cdot)$ denotes the largest singular value of a matrix. In the case of vector inequalities, the inequality holds element-wise. Joint variable dependent upper bound values were assumed.

Using the upper bounds of the modeling uncertainties, the threshold value for the decision signal defined in (17) can be formulated as:

$$\begin{aligned} th = \Delta\sigma(\mathbf{q})\left(\dot{\mathbf{q}}(t)^T\dot{\mathbf{q}}(t) - \dot{\mathbf{q}}(t-T)^T\dot{\mathbf{q}}(t-T)\right) + \\ + \int_{t-T}^{t} \dot{\mathbf{q}}^T \left(\Delta\tau_F(\dot{\mathbf{q}}) + \Delta\mathbf{G}(\mathbf{q})\right) d\xi. \qquad (19) \end{aligned}$$

Remark 1: The proposed detector algorithm calculates the integral of the mechanical power induced by the fault, which is the scalar product of the joint velocity vector and the fault torque vector ($\dot{\mathbf{q}}^T\mathbf{f}$). Accordingly the fault can be properly detected if the vector $\mathbf{f}$ is not perpendicular to the joint velocity vector $\dot{\mathbf{q}}$. This condition is satisfied in the case of the actuator faults. However in the case of collision type faults (the robot collides accidentally with objects in its environment), the force generated by the collision may be perpendicular to the joint velocity vector. Hence the direct applicability of the energetic fault detection for collision detection is limited [20].

B. Fault isolation and identification

After detecting the existence of the fault, it has to be recognized, in which joint actuator the fault occurred and which fault type generated the irregular behavior (fault isolation). The magnitude of the fault should also be obtained in order to handle correctly the fault event (fault identification).

Similar to [12], consider the m dimensional vector set of the possible *fault patterns* that may occur in the system:

$$\mathcal{F} = \{\mathbf{f}_1(\mathbf{q}, \dot{\mathbf{q}}, \tau), \ldots, \ \mathbf{f}_j(\mathbf{q}, \dot{\mathbf{q}}, \tau), \ldots \mathbf{f}_m(\mathbf{q}, \ \dot{\mathbf{q}}, \tau)\}. \quad (20)$$

Note that usually each n dimensional fault vector $\mathbf{f}_j$ contains same elements since the joints of the robots are equipped with same actuator types which may face similar faults.

Assume that in the ith joint of the robot the jth type fault occurred and the residual signal overpasses the threshold th in the time instant t_F and the system operates in faulty mode in the time interval $(t_f, t_f + T_F)$. The evolution in time of the energy induced by this fault can be calculated as:

$$\begin{aligned} E_{Fij}(t) &= K_{Fij} e_{ij}(t), \quad (21)\\ e_{ij}(t) &= \left\{ \int_{t_F}^{t_F+t} \dot{q}_i f_{ji} d\xi | \ t \in (0, T_F) \right\}. \end{aligned}$$

The unknown parameter K_{Fij} characterizes the magnitude of the fault.

Define the $n \cdot m$ dimensional set of *fault energy patterns* induced by the elements of the fault pattern vectors from the set $\mathcal{F}$:

$$\mathcal{E}_F = \{e_{11}(t), \ e_{12}(t), \ \ldots, \ e_{1m}(t), \ \ldots, \ e_{nm}(t)\}. \quad (22)$$

The elements of the set $\mathcal{E}_F$ contain the basic features of the energies of all possible faults that may appear in the system.

Fault Isolation: The evolution in time of the residual signal r_E contains the characteristic of the energy generated by the actual fault. Accordingly, for fault isolation the residual signal has to be compared with each element of the function set $\mathcal{E}_F$.

The comparison can be done by using the correlation coefficient. Consider that the time evolution of the residual signal r_E and the elements of $\mathcal{E}_F$ are given as real, discrete-time vectors with uniformly sampled values with sampling period T_s. Accordingly the length of the vectors is $N = T_F/T_s$. Accordingly the correlation coefficient between the residual signal and the fault energy pattern e_{ij} can be calculated using the standard formula:

$$\sigma_{r_E, e_{ij}} = \quad (23)$$
$$\frac{N \sum_k r_{Ek} e_{ijk} - \sum_k r_{Ek} \sum_k e_{ijk}}{\sqrt{N \sum_k r_{Ek}^2 - (\sum_k r_{Ek})^2} \sqrt{N \sum_k e_{ijk}^2 - (\sum_k e_{ijk})^2}}.$$

If $\sigma_{r_E, e_{ij}}$ is greater than a predefined threshold value $th_1 > 0$, it can be concluded that the fault with the energy pattern e_{ij} is present in the system.

Note that the correlation coefficient is independent of the magnitude and origin of the signals.

Fault Identification: Once the fault is isolated, the magnitude of it related to the corresponding fault can be determined by dividing the mean of the discrete-time evolution of the actual fault with the mean of the discrete time evolution of the isolated fault pattern energy:

$$K_{Fij} = \frac{\sum_k r_{Ek}}{\sum_k e_{ijk}}. \quad (24)$$

Note that the sufficient condition for fault identification is that $\sum_k e_{ijk} \neq 0$.

Multiple Faults: There could be scenarios when simultaneously more than one joint of the robot is in fault mode. For such cases the energetic residual signal contains the characteristics of all the active faults (more than one). Accordingly, more than one correlation coefficient $\sigma_{r_E, e_{ij}}$ will overpass the predefined threshold value th_1.

Consider that a number of L fault energy patterns have reached the level th_1. In order to identify the contribution of each fault energy pattern to the detected fault solve the following optimization problem:

$$min_{K_{Fl}} \left(r_E(t) - \sum_{l=1}^{L} K_{Fl} e_l(t) \right)^2. \quad (25)$$

As in the case of the single faults, assume that the evolution in time of the residual and the corresponding fault energy patterns are given as real, discrete-time vectors with uniformly sampled values. In this case the optimization problem above is a standard linear Least Square problem.

For the case when no correlation coefficient reaches the threshold value th_1, the detected fault does not correspond to any of the fault patterns from the set $\mathcal{F}$, the fault is unknown.

Remark 2 (Isolability): For a correct isolation of the faulty behavior the fault energy patterns in the set $\mathcal{E}_F$ should be distinguishable. The similarity of the energy pattern signals can be tested by calculating the correlation coefficient for each element pair from the set given by (22). For the isolability it should be checked if the calculated correlation coefficients are near to 1. If, for example, $\sigma_{e_{ij}, e_{kl}}$ is near to 1, one of the elements from the corresponding signal pair has to be omitted from the set $\mathcal{E}_F$, since in the time interval $(t_F, t_F + T_F)$ the fault energy patterns e_{ij} and e_{kl} are not distinguishable. After omitting one signal from each non-isolable pair the truncated fault power set is obtained, which has to be used during fault isolation.

IV. Simulation results

The fault detection and isolation method presented in the previous Section was tested on a 2 DOF serial manipulator with two rotational joints. The dynamic model of these manipulators can be found in many textbooks and papers, see e.g. [8]. The following geometrical and dynamic parameters of the robot arm were supposed, all in SI units: length of the segments $l_1 = l_2 = 1 \ m$, position of the center of gravity of the segments $l_{c1} = l_{c2} = 0.5 \ m$, mass of the segments $m_1 = m_2 = 5 \ kg$, inertia of the segments $I_{1zz} = I_{2zz} = 1 \ kgm^2$, $g = 9.81 \ m/s^2$. The friction in the joints was modeled using the Coulomb+viscous model (2) with parameters $F_{Ci} = F_{Vi} = 1, \ i = 1, 2$.

During the simulation experiments the prescribed trajectory of the robot contained acceleration, deceleration and constant velocity phases both in the positive and negative velocity regimes for both joints. The motion of the robot joints is shown in Figure 1. High gain PID control algorithms

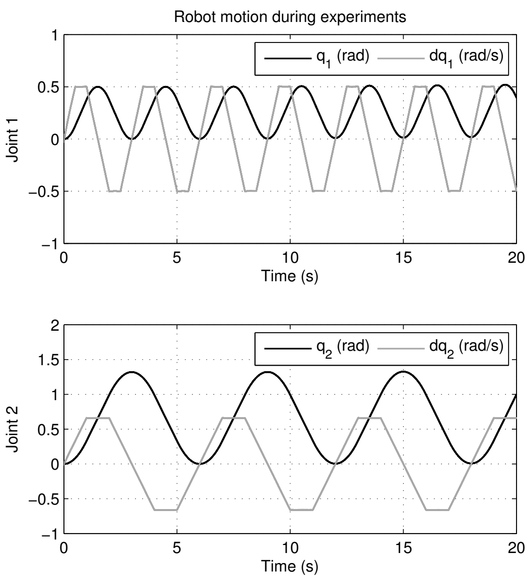

Fig. 1. Joint variables and velocities during fault detection

were applied to keep the joint variables on the prescribed track.

Two fault types were considered in both joints of the robot: increased motion resistance (simulated using the equation (11)) and loss of efficiency (implemented using the equation (12)). In order to demonstrate the sensitivity of the detector on small magnitude faults, 5% efficiency loss was considered. In the case of increased motion resistance type fault, the magnitude was chosen such to be 10% of the maximum value of the control torque during the simulation experiments.

The simulation experiments lasted 20 seconds. The fault events rose in the 10th second of the simulation.

In the first experiment it was considered that an increased motion resistance type fault rose in the joint 1. In the second experiment the second joint's behavior was modified by a loss of efficiency type fault.

Figures 2 and 3 show that the generated faults have small influence on the control performance (tracking error), they can be considered partial faults. However they modify the energy balance of the control system substantially, the energy intake increases. Hence the residual signals, calculated using the relation (16), show that the energy balance of the control system is disturbed due to the faults. For fault isolation, the correlation coefficients were also calculated, using the relation (23). The evolution of the residual and the corresponding fault energy patterns were calculated based on measurements from the time period $10s \ldots 20s$. For the corresponding faults the values of the calculated correlation coefficients were over 0.95.

Simulations were also performed for the case when more than one fault affect the system behavior simultaneously. For this case the calculated correlation coefficients are summarized in the Table I. The correlation coefficients for the

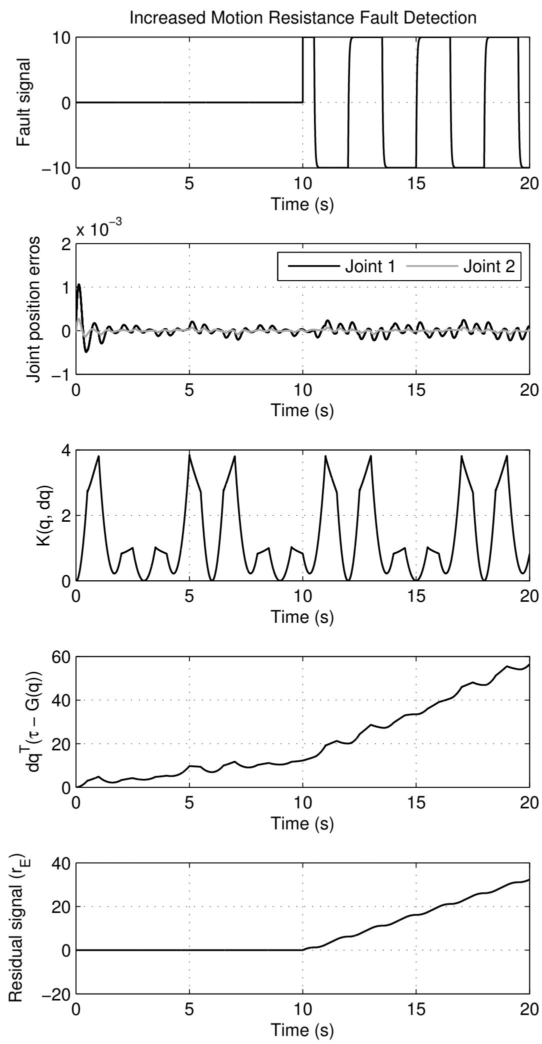

Fig. 2. Increased motion resistance detection in joint 1

active faults are highlighted in the Table. As it can be seen in the case of the active faults the corresponding correlation coefficients are always greater than 0.3.

J1 - f_1	J1 - f_2	J2 - f_1	J2 - f_2
0.5630	0.0208	**0.9421**	0.0694
0.1117	**0.9847**	0.0382	**0.5299**
0.9310	0.0681	0.1119	**0.3607**
0.1205	**0.6070**	**0.7976**	0.2253

TABLE I
FAULTS: f_1 - INCREASED RESISTANCE, f_2 - LOSS OF EFFICIENCY

V. CONCLUSIONS

In this work the problem of fault detection and isolation in robot actuators was solved based on energy monitoring

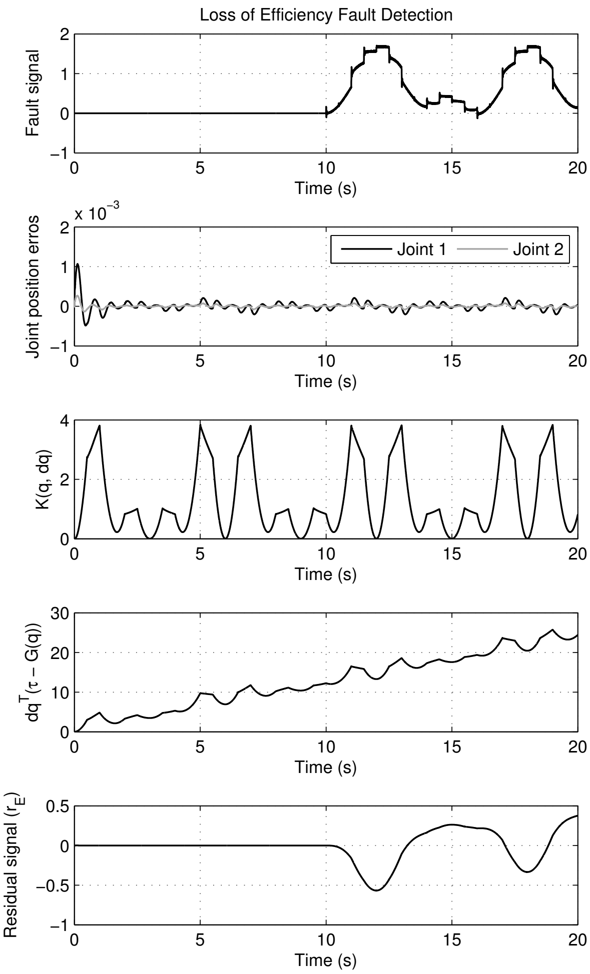

Fig. 3. Loss of efficiency detection in joint 2

of the robot control system. The faults were analyzed from energetic point of view. The advantages of the proposed method are: the residual generation does not depend on the acceleration of the robot; the attenuation of high frequency noises of the actuator is an inherent property of the detector, the filtering properties can easily be tuned with only one parameter; the isolation and identification of the faults can be solved using standard signal processing methods. Simulation results showed that the proposed method can efficiently and reliably detect and isolate different faults in the actuators of the robotic system.

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