FAULT DETECTION AND LOCATION IN MRAC ROBOTIC SYSTEMS

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ABSTRACT. Fault detection, identification and monitoring plays a primary role in systems engineering. In this paper the problem of fault detection in Model Reference Adaptively Controlled (MRAC) robotic systems is investigated. The MRAC model assures convergence to suitable reference models for a class of processes, one of which is the manipulator. However, sudden changes, modelled as faults, in the process parameters may lead to degradation of performance and even to instability. Using the Discrete Square Root Filter (DSF) it is possible to monitor the performance of the system and make the appropriate decisions in the event of a failure. The whole fault monitoring scheme is easily added to an existing MRAC system. Simulation studies in the case of faults in the manipulator's D.C. motors complete the paper and demostrate the usefulness of the method.

1. INTRODUCTION

The increasing demands on reliability and safety of industrial processes and their elements lead to the development of methods for improving the supervision and monitoring as part of the overall control of the process. This is also true for fine processes with highest demands on reliability and safety, e.g. the robotic manipulators {1-7}.

In the next sections the elementary functions of process supervision are cosidered. The methods for faults detection are described for the DC - motor actuators of a robotic manipulator.

A fault is to be understood here as a nonpermitted deviation of a physical parameter from the nominal value which leads to the inability to fulfil the intended purpose. After the effect of a fault is known, a decison on the action to be taken can be made. If the fault is evaluated to be tolerable, the operation may continue and if it is conditionally tolerable a change of operation has to be applied. However if the fault is not tolerable the operation must be immediately stopped and the fault eliminated.

S. Tzafestas et al. (eds.), System Fault Diagnostics, Reliability and Related Knowledge-Based Approaches, Vol. 1, 203–217.

2. DYNAMIC MODELS FOR THE MRAC ROBOTIC MANIPULATOR

A lot of results on the control problem of robotic manipulators have been derived and widely disseminated. Among the control algorithms developed, the so called **Model Reference Adaptive Control** (MRAC) approach seems to provide a robust method for the control of processes with variable parameters and/or unknown parts.

Nicosia and Tomei {1} use the complete nonlinear time varying model including all second order terms, resulting from a generalized application of Lagrangians dynamics, to derive a robust MRAC algorithm for the manipulator based on Popov's hyperstability theory. In their paper the DC-motor actuators'dynamics are neglected resulting in sudden fractuations for the derived control torques.

Tzafestas and Stavrakakis {2} extended this original approach by introducing the DC-motors'dynamics with some improvement concerning the on line calculation of the controller parameters. The results can be compared with those obtained in {1}. It is easy to see that the DC-motor dynamics are taken into account for the control voltage calculation, the control voltage is smooth and easier to apply in practice than the control torque proposed in {1}. The global dynamic model of a **3-dof** (degrees of freedom) robotic manipulator is derived based on the Lagrangian approach and the dynamic equations for the armature circuit and the mechanics of the actuators DC-motors. These equations have the following form (see Fig. 1):

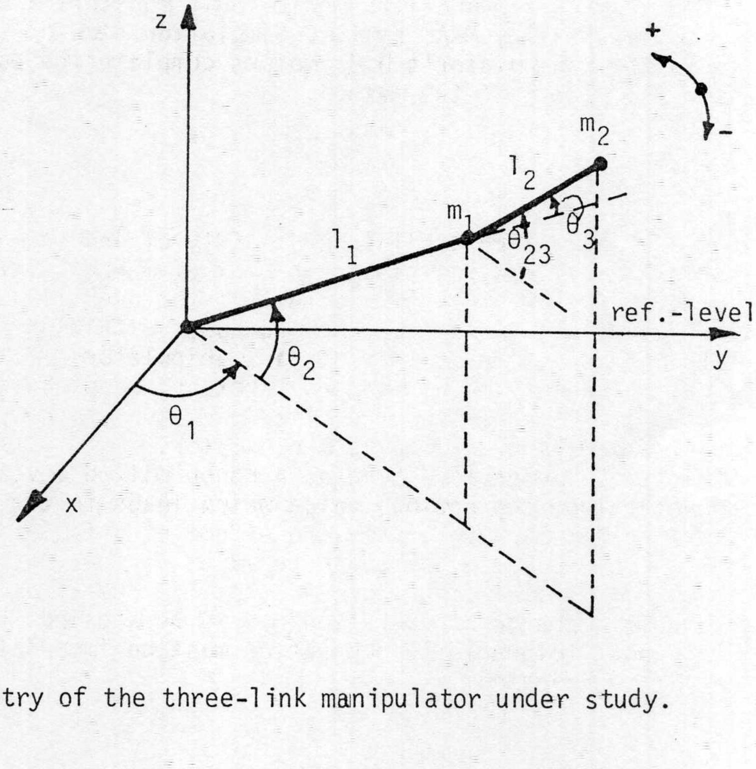

Fig.1. Geometry of the three-link manipulator under study.

$$\begin{bmatrix}\dot{T}\\ \dot{\omega}\end{bmatrix}=-G^*(\theta)\{C^*(\theta)h^*(\omega,T)-\Gamma^*(\theta)\}+G^*(\theta)\,S\,V \qquad (1)$$

where: $\theta^T(t)=[\theta_1(t)\ \theta_2(t)\ \theta_3(t)]$, $V^T(t)=[V_1(t)\ V_2(t) V_3(t)]$

$$\omega^T=[\dot{\theta}_1\ \dot{\theta}_2\ \dot{\theta}_3]$$

$$G^*(\theta)=\begin{bmatrix}K_{mN} & 0\\ 0 & G(\theta)\end{bmatrix}\varepsilon R^{6x6},\quad C^*(\theta)=\begin{bmatrix}0 & I & K_{mN}^{-1} & K_{RL}\\ D(\theta) & RN & & -I\end{bmatrix}\varepsilon R^{6x12}$$

$$h^*(\omega,T)=\begin{bmatrix}h(\omega)\\ \omega\\ T\end{bmatrix}\varepsilon R^{12},\quad \Gamma^*(\theta)=\begin{bmatrix}0\\ \Gamma(\theta)\end{bmatrix}\varepsilon R^{6},\quad S=\begin{bmatrix}-K_{mN}^{-1}K_{mL}\\ 0\end{bmatrix}\varepsilon R^{6x3}$$

with

$$K_{mN}=\text{Diagonal}\left[\frac{K_{mi}^2N_i^2}{L_i}\right],\ K_{RL}=\text{Diagonal}\left[\frac{R_i}{L_i}\right],\ N=\text{Diagoanl}\left[N_i\right]$$

$$R=\text{Diagonal}\left[\rho_i\right],\ K_{mL}=\text{Diagonal}\left[\frac{K_{mi}N_i}{L_i}\right],\ J_m=\text{Diagonal}\left[J_{mi}\right],\ i=1,2,3$$

$$G(\theta)=\left[A(\theta)+J_mN\right]^{-1}$$

The symbols used have the following meaning:

N_i, K_{mi}, R_i, L_i (i=1,2,3): are the gear ratio, the DC torque constant, the armature resistance, the armature inductance of the DC-motors, respectively.

V_i : is the armmture voltage (control input) of the ith DC-motor

ρ_i : is the viscous friction coefficient of the ith DC-motor

J_{mi} : is the moment of inertia of the rotor of the ith DC-motor

$\omega_{mi}=N_i\dot{\theta}_i=N_i\omega_i$: is the reflected shaft angular velocity

$A(\theta)$: is the (3x3) generalized inertial matrix which is symmetric and positive definite.

$\Gamma(\theta)$: is the (3x1) vector of the gravitational torques

$D(\theta)h(\dot{\theta})$: involves the centrifugal and the Coriolis torques.

(with $h(\dot{\theta})$=vector of $\dot{\theta}_i\dot{\theta}_j$, i=1,2,3, j=i,...,3

$i_i(t)$: is the armature current of the ith joint actuator

$T_i(t)=K_{mi}N_i i(t)$: is the reflected electromagnetic torque of the ith joint actuator

$T_{Li}(t)=T_i(t)-J_{mi}\dot{\omega}_{mi}-\rho_i\omega_{mi}$: is the torque generated at the ith joint (reflected load of the ith DC motor)

The **MRAC** algorithm which provides a robust trajectory following method of robots using the DC-motor actuators dynamics is fully presented in {2}.

The values of the DC-motors constants play important role for the calculation of the control law at any instant. On the other hand the correct operation of the whole robot depends strongly on the correct operation of the DC-motor actuators i.e. on the conservation of their physical properties (parameters) during operation.

Sudden changes of the physical parameters of the actuators which may must, therefore, be automaticaly monitored in order to achieve a reliable and safe operation of the manipulator.

3. FAULT MONITORING FOR THE DC-MOTOR ACTUATORS OF A ROBOT

The Model Reference Adaptive Controlled robotic system described in the previous section must be supervised automaticaly. The first stage of this supervision consists of the detection of changes (faults) in the dc motor actuators based on theoretically derived motor models and parameter estimation. After the effect of the fault is known, a decision on the action to be taken can be made. In {3} - {7} many methods of fault monitoring in industrial processes are reported. The generalized structure of fault detection methods is given in Fig.2 and involves three distinguished stages.

In many cases, the following variables can be assumed to be given:

— Measurements of the input **y**(t) and the output **u**(t) of the process.
— More or less exact a-priori information about the static and dynamic behaviour of the process.

3.1. Mathematical model for the DC-motor actuator

The dynamic model for the DC-motor actuator is given analyticaly in Appendix I. Define $\mathbf{u}^T(t)=\left[V_i(t) \quad T_{Li}(t)\right]$, $\mathbf{y}(t)=\left[i_i(t) \quad \omega_i(t)\right]^T$. Then the model ($I_1$) of appendix I can be formulated as a Continuous-Time **Multi-Input Multi-Output** (MIMO) of two (r=2) differential equations, for the actuator of each link. That is:

$$\mathbf{y}^{(1)}(t)+A_1\mathbf{y}^{(1)}(t)+\mathbf{A}_0 y(t)=b_0\mathbf{u}(t) \qquad (2)$$

where:

$$A_1=\mathbf{0}\in\mathbf{R}^{4x4},\ \mathbf{A}_0=\begin{bmatrix} \frac{R_i}{L_i} & \frac{K_{mi}N_i}{L_i} \\ -\frac{K_{mi}}{J_{mi}} & \frac{\rho_i}{J_{mi}} \end{bmatrix},\quad b_0=\begin{bmatrix} \frac{1}{L_i} & 0 \\ 0 & -\frac{1}{J_{mi}N_i} \end{bmatrix}$$

Define: $\theta_1=\frac{R_i}{L_i}$, $\theta_2=\frac{K_{mi}N_i}{L_i}$, $\theta_3=\frac{1}{L_i}$, $\theta_4=-\frac{K_{mi}}{J_{mi}}$, $\theta_5=\frac{\rho_i}{J_{mi}}$, $\theta_6=-\frac{1}{J_{mi}N_i}$

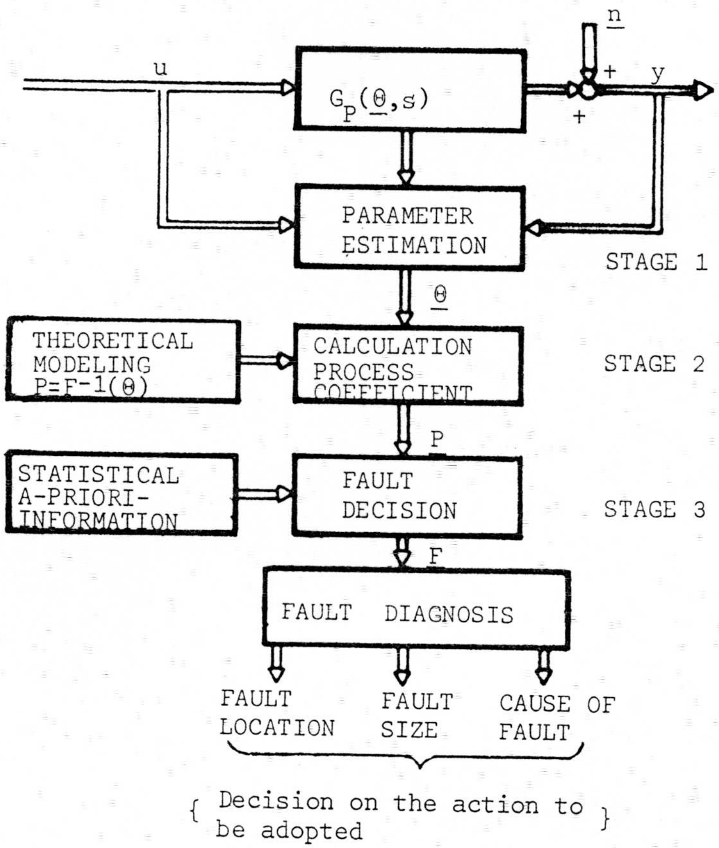

Fig. 2. Generalized structure of fault detection method.

i.e. $\theta^T = \begin{bmatrix} \theta_1 & \theta_2 & \theta_3 & \theta_4 & \theta_5 & \theta_6 \end{bmatrix} \varepsilon \mathbf{R}^6$

Then, if measurements of $\mathbf{y}(t)$ and $\mathbf{u}(t)$ are available equation (2) leads to:

$$\mathbf{e}(t) = \mathbf{y}^{(1)}(t) - \boldsymbol{\Psi}(t)\theta \tag{3}$$

with

$$\Psi(t)=\begin{bmatrix} -\mathbf{y}^T(t) & u_1(t) & \mathbf{0} & 0 \\ 0 & 0 & -\mathbf{y}^T(t) & u_2(t) \end{bmatrix} \quad \mathbf{R}^{2x6}$$

3.2. Process parameter estimation using a discrete Square-root filter (DSF)

In this stage, measurements of the input and output signals are considered to be available at discrete times $t=kT_0$, $k=1,2,\ldots,N$ with T_0 the sampling time. This means, that measurements of $i_i(k)$, $\omega_i(k)$, $V_i(k)$, $T_{Li}(k)$, $k=0,1,\ldots,N$ are available.

In the present case of the 3-DOF MRAC robot these measurements are obtained through simulation (numerical integration) of the complete robot model (1), where the input voltage $\mathbf{V}(t)$ is deremined via the control algorithm proposed in {2} in order to follow the desired trajectories.

The parameter estimation requires the first order time derivatives of the noisy output signal $\mathbf{y}(t)$. These derivatives can be calculated from the sampled measurements $\mathbf{y}(k)$ using numerical differentation. The simplest way is to replace the derivatives by the corresponding (backward) differences. To reduce the influence of the noise interpolation formulas, interpolation by third-order polynomials or Newton interpolation can be used. For calculating higher-order derivatives the use of state variable filtering is recommended {3}.

The **Discrete Square Root Filtering** (DSF) method combined with a moving window of N samples over the data, provides a better method than the classical **RLS** for the detection of parameters changes. This is due to the numerical properties of the **DSF**. For details refer to Kaminski et.al. {5}.

By observing the **MIMO**-linear continuous-time system over $k=1,2,\ldots,N$ samples the following discrete time set of N equations is obtained from the continuons time system (3):

$$\begin{aligned} \mathbf{e}(1)&=\mathbf{y}^{(1)}(1)-\Psi(1)\theta \\ \mathbf{e}(2)&=\mathbf{y}^{(1)}(2)-\Psi(2)\theta \\ &\cdots\cdots\cdots\cdots \\ \mathbf{e}(N)&=\mathbf{y}^{(1)}(N)-\Psi(N)\theta \end{aligned} \tag{4}$$

or

$$E(N)=Y^{(1)}(N)-\underline{\Psi}(N)\theta \tag{5}$$

with

$$E^T(N)=\left[\mathbf{e}^T(1) \;\ldots\; \mathbf{e}^T(N)\right]\varepsilon\mathbf{R}^{(2Nx1)}$$

$$Y^{(1)^T}(N)=\left[\mathbf{y}^{(1)^T}(1) \;\ldots\; \mathbf{y}^{(1)^T}(N)\right]\varepsilon\mathbf{R}^{(2Nx1)}$$

$$\underline{\boldsymbol{\Psi}}(N)=\begin{bmatrix}\psi(1)\\ \psi(N)\end{bmatrix} \in R^{2N\times 6}$$

The méaning of the moving window of width N over the data is shown by the following definition

$$E(N+i)=\left[\mathbf{e}^T(i+1) \;\ldots\; \mathbf{e}^T(N+i)\right]$$

$$\mathbf{Y}^{(1)}(N+1)=\left[\mathbf{y}^{(1)^T}(i+1) \;\ldots\; \mathbf{y}^{(1)^T}(N+i)\right]$$

$$\underline{\boldsymbol{\Psi}}(N+i)=\begin{bmatrix}\boldsymbol{\psi}(i+1)\\ \vdots\\ \boldsymbol{\Psi}(N+i)\end{bmatrix} \qquad \text{for } i=0,1,2,\ldots$$

The parameters $\boldsymbol{\theta}$ can be estimated by minimizing the cost function V(i):

$$V(i)=||\mathbf{E}(N+i)||^2 = \sum_{k=1+i}^{N+i} e^T(k)\mathbf{e}(k) \qquad \text{for } i=0,1,2,\ldots \quad (6)$$

Let us define

$$S(N+i)=\Big[\underbrace{\Psi(N+i)}_{6} \quad \underbrace{\mathbf{Y}^{(1)}(N+i)}_{1}\Big]\Big\}2N \text{ and } \boldsymbol{\theta}^*=\begin{bmatrix}-\boldsymbol{\theta}\\ \hline I\end{bmatrix} \in R^7$$

Then, the condition (6) becomes:

$$\min_{\boldsymbol{\theta}} V(i)=\min_{\theta}||S(N+i)\theta^*||^2 \quad i=0,1,2,\ldots \qquad (7)$$

The least squares estimator of the parameter vector $\boldsymbol{\theta}$ is then given by the well-known estimation equation:

$$\hat{\theta}_{N+i}=\left[\boldsymbol{\Psi}^T(N+i)\Psi(N+i)\right]^{-1}\Psi(N+i)\mathbf{y}^{(1)}(N+i) \;, \quad i=1,2,\ldots \qquad (8)$$

This equation is not recursive and the parameters are biased for any type of noise $\mathbf{e}(t)$.

The basic idea of the Discrete Square Root Filtering applied here is as loffows:

Given:

$$\mathbf{S}(N+i)\boldsymbol{\theta}^*=\mathbf{E}(N+i)$$

Find an orthogonal transformation $\mathbf{T}\in\mathbf{R}^{2N\times 2N}$ such that

$$\mathbf{T}(N+i)\mathbf{S}(N+i)=\begin{bmatrix}\overbrace{\mathbf{W}(N+i)}^{7}\\ \hline \mathbf{0}\end{bmatrix}\begin{matrix}\}7\\ \}2N-7\end{matrix} \;, \quad \mathbf{T}(N+i)^T\mathbf{T}(N+i)=\mathbf{I},\; i=0,1,2,\ldots \qquad (9)$$

where $\mathbf{W}(N+i)$ is upper triangular, or, equivalently, find $\mathbf{W}(N+i)$ and $E'(N+i)=\mathbf{T}(N+i)\mathbf{E}(N+i)$ directly.

This transformation does not change the cost function, i.e.

$$V(i)=||\mathbf{E}(N+i)||^2=||\mathbf{T}(N+i).\mathbf{E}(N+i)||^2=||\mathbf{E}'(N+i)||^2 \qquad (10)$$

From (10) it follows directly that:

$$V(i)=\left\| \mathbf{E}'(N+i) \right\|^2 = \left\| \begin{array}{c} \mathbf{E}_1'(N+i) \\ \hline \mathbf{E}_2'(N+i) \end{array} \right\|^2 = \left\| \begin{bmatrix} \mathbf{W}_{\theta\theta}(N+i) & \mathbf{W}_{\theta E}(N+i) \\ \mathbf{\Omega} & \mathbf{W}_{EE}(N+i) \end{bmatrix} \begin{bmatrix} -\boldsymbol{\theta} \\ \mathbf{1} \end{bmatrix} \right\|^2 \quad (11)$$

where $\mathbf{W}_{\theta\theta} \varepsilon \mathbf{R}^{6x6}$, $\mathbf{W}_{\theta E} \varepsilon \mathbf{R}^{6x1}$ and $\mathbf{W}_{EE} \varepsilon \mathbf{R}$ i.e.

$$\mathbf{W}(N+i)=\begin{bmatrix} \mathbf{W}_{\theta\theta}(N+i) & \mathbf{W}_{\theta E}(N+i) \\ \mathbf{\Omega} & \mathbf{W}_{EE}(N+i) \end{bmatrix}$$

and $\mathbf{W}_{\theta\theta}$ is also upper triangular.

Eq. (11) implies that:

$$\min_{\boldsymbol{\theta}} V(i)=\min_{\boldsymbol{\theta}} \| \mathbf{E}_1'(N+i) \|^2$$

where

$$-\mathbf{W}_{\theta\theta}(N+i)\boldsymbol{\theta}+\mathbf{W}_{\theta E}(N+i)=0$$
$$\mathbf{E}_2'(N+i)=\mathbf{W}_{EE}(N+i) \quad (12)$$

Eq. (12) leads to the following estimator of $\boldsymbol{\theta}$:

$$\hat{\boldsymbol{\theta}}(N+i)=\mathbf{W}_{\theta\theta}^{-1}(N+i)\mathbf{W}_{\theta E}(N+i) \quad (13)$$

and the minimmum value of V(i) is given by $\mathbf{W}_{EE}(N+i)$, i=0,1,2,.... Choosing the appropriate **T** may be interpreted as "compressing" the data matrix **S** into the upper triangular matrix **W**. The triangular form of **W** facilitates the computation of $\mathbf{W}_{\theta\theta}^{-1}$ and reduces the dimension of the matrix to be inversed compared with eq. (8). Schmidt derived an algorithm for constructing the transformation matrix T which is given in Appendix II of Kaminski et al. {5}.

3.3. Calculation of the process physical coefficients

The physical process coefficients of the simulated robot DC-motor actuators were selected to be:

$p_1=R_i$	$p_4=J_{mi}$	Vmax=12V
$p_2=L_i$	$p_5=\rho_i$	
$p_3=K_{mi}$	$N_i=64$	

These are values in the range of the coefficients for DC-motor drives found in the literature.

The relation ship between process model parameters and physical process coefficients **p** is given by:

$$p_1 = \frac{\theta_1}{\theta_3} \qquad (14.a)$$

$$p_2 = \frac{1}{\theta_3} \qquad (14.b)$$

$$p_3 = \frac{\theta_2}{\theta_3 N_i} \qquad (14.c)$$

$$p_4 = \frac{-\theta_2}{N_i \theta_4 \theta_3} \quad (14.d) \text{ and also } p_4 = -\frac{1}{\theta_6 N_i} \qquad (14.e)$$

$$p_5 = -\frac{\theta_2 \theta_5}{\theta_4 \theta_3 N_i} \qquad (14.f)$$

The case of a fault occurence into the gear box is considered as an event w.p. 0. Under this consideration the relations (14.a) to (14.f) hold for the physical process coefficients. However, the case of a fault in the gear box i.e. modification of the no-fault value of the gear ratio can be detected via the fault occurence or not in the parameters p_3, p_4, p_5 of the 4th stage.

The physical process coefficient vector **p** will be used in stage 3 of the on line fault identification method as input data.

3.4. Fault detection and identification for the robot DC-motor actuator

Fault detection and identification involves the DECISION that a fault has occured (fault diagnosis), the LOCALIZATION of the fault and of his cause and the ESTIMATION of the fault size.

After calculation of the physical process coefficients $\mathbf{p}(k)$ in stage 2, let us consider $\mathbf{p}(k)$ as a Gaussian vector with its components statisticaly independent and its realizations $\mathbf{p}(i)$ and $\mathbf{p}(j)$ in the different sample instants $i \neq j$ statisticaly independent. It can be considered that the mean vector $\boldsymbol{\mu}(k) = E\, \mathbf{p}(k)$ and the covariance matrix $\sigma^2(k) = E\left[(\mathbf{p}(k) - \boldsymbol{\mu}(k))\ (\mathbf{p}(k) - \boldsymbol{\mu}(k))^T\right]$ are invariant for the non-error case, i.e.

$$\mu(k) = \left[\bar{\mu}_1 \ldots \bar{\mu}_6\right]^T;\ \text{const.}, \quad \sigma^2(k) = \text{diag}\left[\bar{\sigma}_1^2, \ldots, \bar{\sigma}_6^2\right]:\ \text{const.}$$

Under these conditions the joint probability density function over N samples is defined as:

$$f(\mathbf{p}(1), \ldots, \mathbf{p}(N)) = \prod_{i=1}^{N} f(\mathbf{p}(i)) \qquad (15)$$

A fault is defined by a significant deviation of the mean μ_i and/or variance σ_i^2 of $p_i(k)$ — the i^{th} component of $p(k)$ — from the non-error value $\bar{\mu}_i$, $\bar{\sigma}_i^2$. Moreover, it is considered that only one fault may occur at a time.

This is a classical hypothesis test problem and can be handled by the formulation of (m+1) hypothesis H_i, $0 \leqslant i \leqslant m$, where m=6 in the case of the DC-motor of each robot joint actuator.

$$H_i = \begin{cases} \text{no fault in the mean and/or the variance of } \mathbf{p}\text{: } (i=0) \\ \text{fault of type } i \text{ (significant deviation of mean and/or variance of } p_i\text{), } 1 \leqslant i \leqslant m. \end{cases}$$

Each hypothesis H_i can be assosiated with a Ganssian conditional density function, where $\mu(H_i)$ and $\sigma^2(H_i)$ denote conditional mean and variance for hypothesis H_i. Therefore, the non-error case is described by $\mu(H_o)$, $\sigma^2(H_o)$, whereas $\mu(H_i)$, $\sigma^2(H_i)$, $1 \leqslant i \leqslant m$, describe a fault of type i.

When the no-fault mean and variance are not known i.e. the values fo the parameters are not known a priori, an estimation algorithm of $\mu(H_o)$ and $\sigma^2(H_o)$ is needed.

The output of the fault identification stage is a fault vector:

$$F = \left[i, \hat{\mu}_i(H_i), \hat{\sigma}_i(H_i) \right]^T, \quad 1 \leqslant i \leqslant m \tag{16}$$

where i represent the type of error, characterized by $\hat{\mu}_i(H_i)$ and $\hat{\sigma}_i(H_i)$. The fault detection and localization is possible by computing the **Logarithmic Likelihood Ratios**. The algorithm used here for estimating the non-error statistics and the fault detection and localization is reported with details in 4 .

4. SIMULATION RESULTS

The physical process coefficients of the simulated DC-motor robotic actuator are:

$R=1.1\Omega$	$J_m=0.001$ Kgm^2
$L=1$mH	
$K_m=0.0224$ Vsec	$p=0.1\frac{\text{kgm}^2}{\text{sec}}$

These values give the a-priori knowlege of the actuator parameters used for the calculation of the **MRAC** controller appled on the robot in 2 .

The simulation of the effect of a fault on the resistance R at sample time k=105 msec on the MRAC controller performance is shown in fig. 8. Figures 3÷5 show the performance of the controller and the fault detector in the normal case. Figures 6 and 7 show the performance of the fault detector which operates very well.

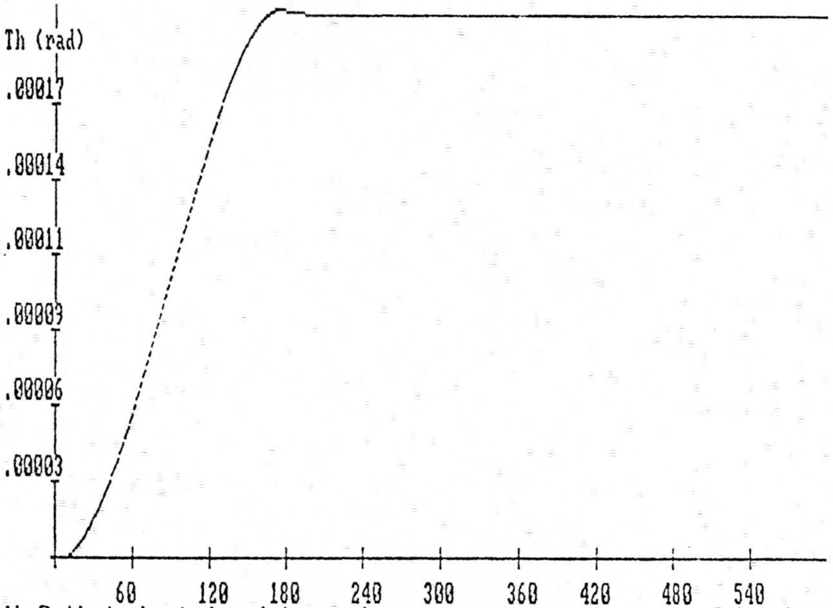

fig.3 |desired-actual angle|, normal case

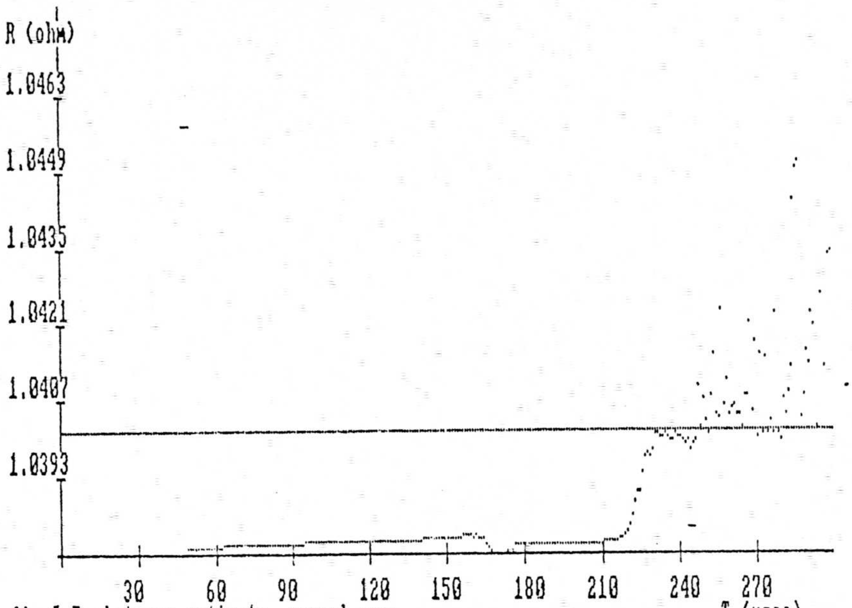

fig.4 Resistance estimate, normal case

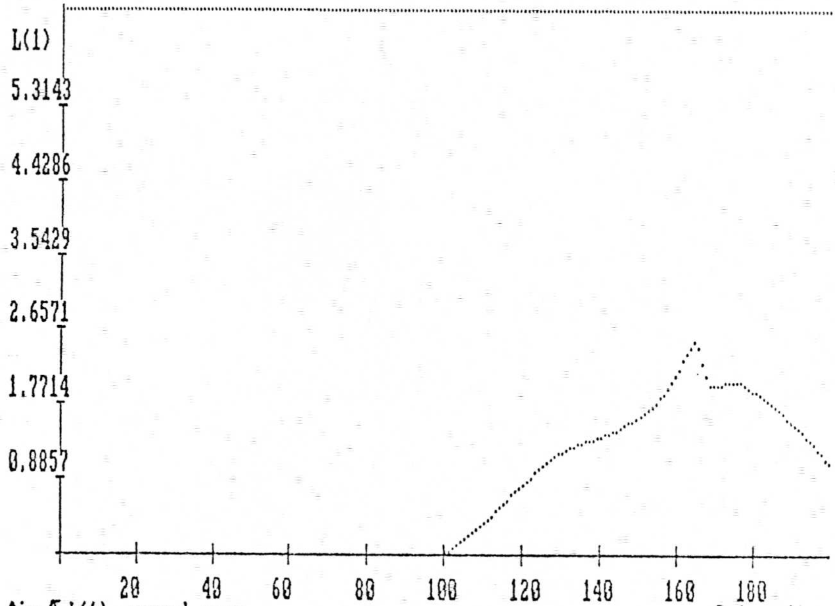

fig.5 L(1), normal case

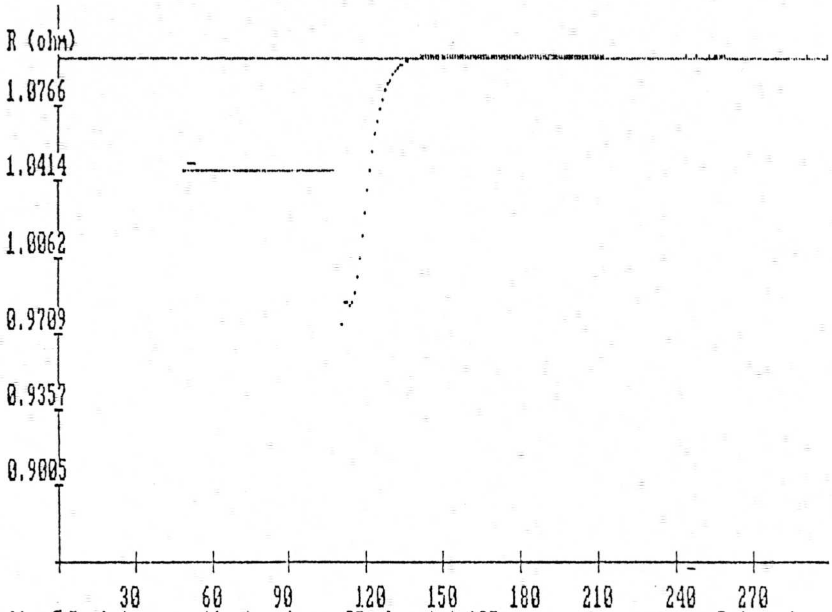

fig.6 Resistance estimate, jump .05 ohm at t=105

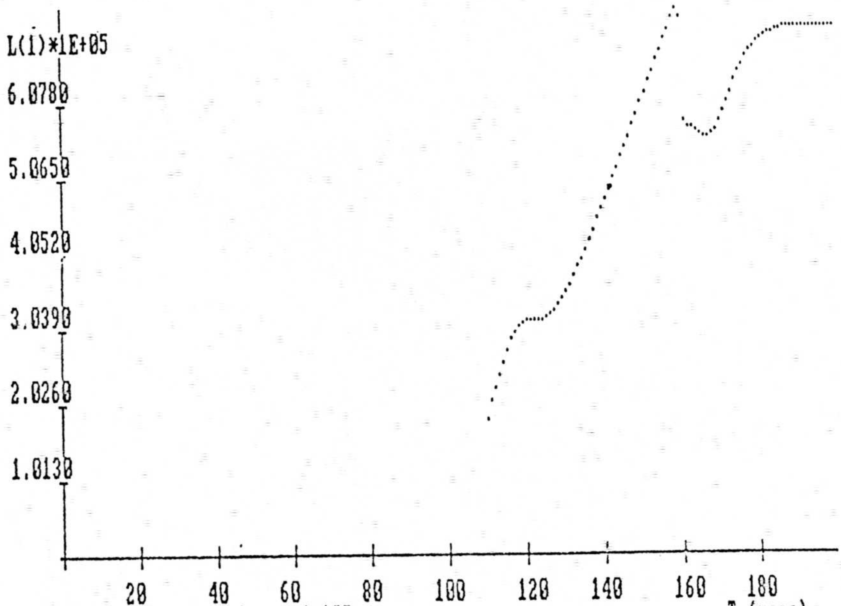

fig.7 L(1), jump 0.5 ohm at t=105

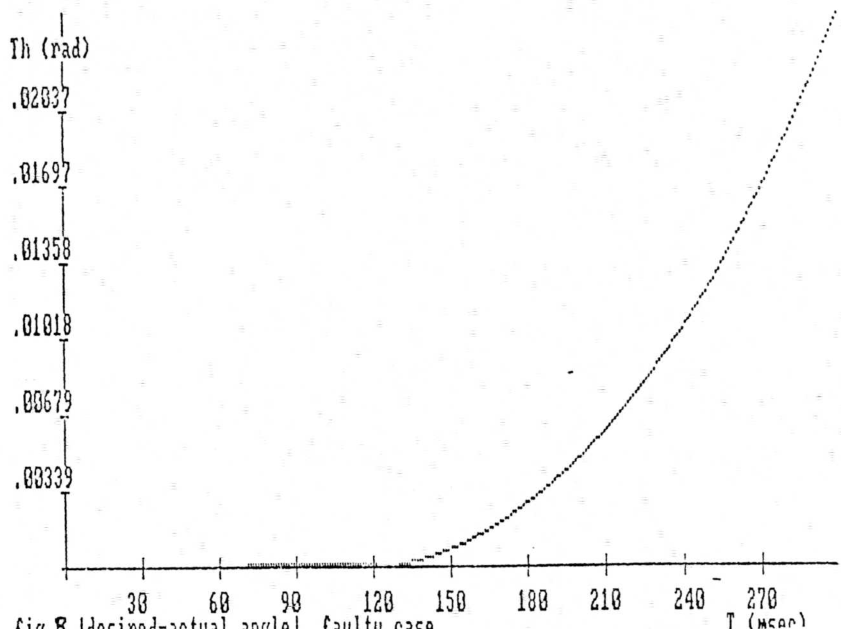

fig.8 |desired-actual angle|, faulty case

5. APPENDIX I:

The dynamic equations for the armature circuit and the mechanics of a d.c. motor leads to the state-space representation for the actuator of the link i of the robot:

$$\begin{bmatrix} \dfrac{di_i}{dt} \\ \\ \dfrac{d\omega_i}{dt} \end{bmatrix} = \begin{bmatrix} -\dfrac{R_i}{L_i} & -\dfrac{K_{mi}N_i}{L_i} \\ \\ \dfrac{k_{mi}}{J_{mi}} & -\dfrac{p_i}{J_{mi}} \end{bmatrix} \begin{bmatrix} i_i \\ \\ \omega_i \end{bmatrix} + \begin{bmatrix} \dfrac{1}{L_i} & 0 \\ \\ 0 & -\dfrac{1}{J_{mi}N_i} \end{bmatrix} \begin{bmatrix} V_{di}(t) \\ \\ T_{Ldi}(t) \end{bmatrix} \qquad (I_1)$$

Where V_{di} is the calculated control voltage from the MRAC controller and T_{Ldi} is the corresponding torque generated at the ith joint.

6. CONCLUDING REMARKS

The present paper constitutes a first piece of work towards the end of applying efficient dynamic fault detection and location algorithms to controlled robotic systems. Regarding the technique presented in this paper we note the following:

— The least squares estimator is very sensitive to parameter and other variations

— The window length is critical for false alarms and missing detections

— The window length should be much larger for meaningful system reorganization

— The response time of the detection scheme must be minimized by using custom hardware.

Some aspects which are currently under study are:

— Comparision of various estimation algorithms with reference to the fault detection and location problem.

— Application of the algorithm (s) to real robotic systems.

— Consideration of the case where noise is present.

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