FAULT DETECTION AND ISOLATION FOR ROBOT MANIPULATORS USING ANFIS AND WAVELET

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ABSTRACT

With the growing technology fault detection and isolation become one of the interesting and important research areas in automatic control. Robots for specified missions like waste treatment in a nuclear reactor or a space walk must be very reliable and this demand forced the researchers adapting FDI methods to robotics. In this study a model based FDI system using Anfis and Wavelet for robot manipulators is proposed.

I. INTRODUCTION

With the growing technology, demand for more reliable and more robust systems with less faults arised. Related to this demand in the beginning of 1970's, the first studies on fault detection of dynamic systems appeared. In 1991, the committee of IFAC SAFEPROCESS is founded and in 1993 this committee issued some definitions about fault detection and isolation (FDI), fault diagnosis and fault tolerant control (FTC) [1].

While the first studies on fault detection were on the supervision of chemical processes, then they were extended to systems with high reliability demand like aero and space vehicles, cars, nuclear reactors and robots. Especially the airplane crashes and nuclear reactor explosions forced researchers to this area.

Robots can be thought as an assistant in many applications. In addition to applications like serial product lines which robots can work harder and faster than humans, they can accomplish missions like waste treatment in nuclear reactors, data and sample collection in underwater and space tasks which can be very dangerous for humans. An occurrence of a fault or an error may cause abortion of a whole mission with big money costs, even it may cause harm to humans. Similarly it may stop the whole product line and may cause a delay of production. Because of these reasons with 1990's studies on robot reliability and fault detection and isolation increased. In addtion to these studies, NASA and US Army issued some standards on robots and on the reliability and fault possibilities of robot parts [2].

Studies and methods on fault detection and isolation can be divided into two main groups, model-based methods and data-based methods [3]. Model-based methods are based on the modelling of the available system and data-based methods are based on the recorded datas taken from the system. Although there are lots of methods for model-based fault detection, the main difference between them is related to the linearity of the system, linear, nonlinear or bilinear. The methods for nonlinear systems are limited and most of them are based on artificial intelligence techniques like neural networks and fuzzy logic which have superiority on non-mathematical modelling. Due to the high nonlinearity of robots, most studies on FDI of robots are focused on AI techniques.

An examination of the literature shows that there are lots of approaches for FDI of robots. Schneider and Frank used robust observers for fault detection and fuzzy logic for residual evaluation/fault isolation [4]. Vemuri and Polycarpou used neural networks to approximate the fault in order to accommodate faults after the occurence of fault [5]. Visinsky et al used analytical redundancies of robot dynamics [6]. Terra and Tinós used some different neural network architectures like RBF and KSOM for residaul generation and evaluation [7].

In this study a robust fault detection and isolation system for robot manipulators which use only position and velocity signals is proposed. For robust control of robot manipulator Computed Torque-PID (CT-PID) method is used. For robot modeling Anfis is used and the residual generation/fault detection part of the system is implemented. For the residual evaluation/fault isolation part of the system, Discrete Wavelet Transform (DWT) is applied to residuals. The detail coefficients obtained from this transform are passed through a decision logic-rule base block and fault isolation part is implemented. The block diagram of the proposed system is given in Fig. 1.

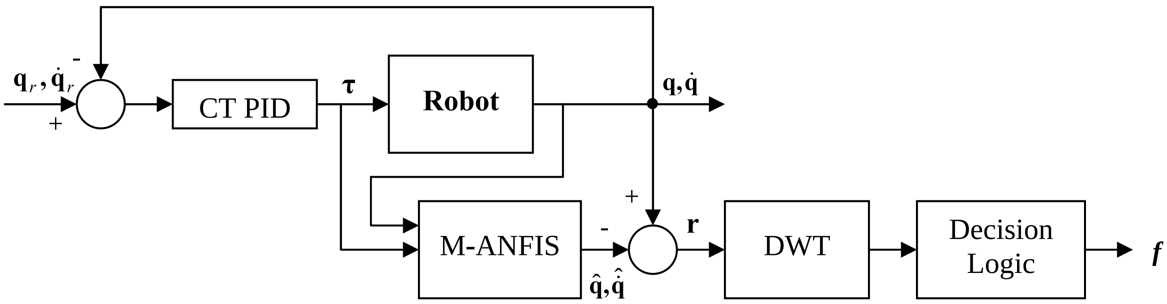


Fig. 1 The block diagram of the proposed system

II. RESIDUAL GENERATION /FAULT DETECTON USING ANFIS/M-ANFIS

Residuals are defined as the difference between the real system and the model of the system. In order to trust residuals the model of the system has to be very precise. One of the methods for robot modeling is Anfis [8]. General structure of Anfis is shown in Fig. 2.

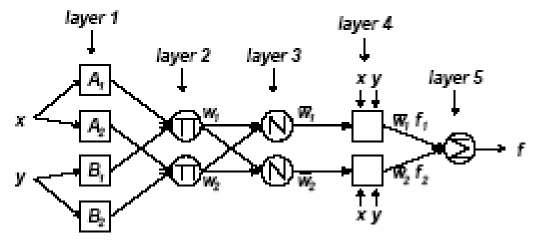


Fig. 2 Structure of Anfis

It can be seen from Fig. 2 that Anfis is constructed on 5 layers. In the first layer the inputs are applied to the rule base defined with membership functions. The parameters used to define membership functions are called premise parameters. In the second layer the membership function values coming from each input multiplied each other and each node value of these multiplications are defined as firing strength of each rule. In the third layer the firing strengths are normalized. In the fourth layer, using each input, a first order function (i.e. $p_i x+q_i y+r$ in Fig.2) is generated and multiplied by normalized firing strengths. The parameters of these first order functions are called consequent parameters. In the fifth layer as the final layer all the signals coming are summed and the output signal is obtained.

The aim of Anfis is to update the parameters in order to obtain appropriate outputs for appropriate inputs. This is proved by using two passes (forward and backward) with different directions and learning methods (hybrid learning). In the forward pass premise parameters are fixed and the inputs are passed forward until fourth layer. Then with least squares consequent parameters are determined. In the backward pass consequent parameters are fixed, the error signal is backpropagated and the premise parameters are updated with gradient descent.

It can be seen in Fig. 2 that the structure of Anfis is MISO. However most dynamic systems have MIMO structure. Therefore for these systems multiple-Anfis (M-Anfis) with independent parameters and outputs are used. Furthermore for MIMO systems a structure called coactive-Anfis (C-Anfis) exists [8]. In this study M-Anfis is preferred. For modeling present torque values and previous position and velocity values are used as inputs and M-Anfis generates present position and velocity values.
The structure of this modeling is shown in Fig. 3.

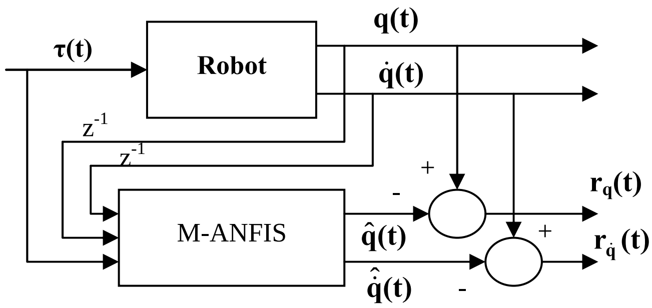


Fig. 3 Residual generation with M-Anfis

According to Fig. 3 if a robot with 3 link is considered there will be 2 Anfis for position and velocity values of each link. As a result for this robot model 6 different Anfis are needed

To generate residuals the difference between robot model and real robot is taken. Exceeding the threshold of these residuals can be thought as an indicator of an unexcepted situation like fault.

III.RESIDUAL EVALUATION/FAULT ISOLATION USING WAVELETS

Residual generation is followed by fault isolation which isolate faults from each other according to residual evaluation. This operation is based on the fact that each fault shows different residual characteristics. For nonlinear systems artificial intelligence techniques which are used for classification and pattern recognition are always used for this operation.

In this study Wavelet transform is used for fault isolation. Wavelet tranform deviates from Fourier transform that it can represent the frequency components of the signal in time domain. The Wavelet transform is given in Eq. 1 [9]:

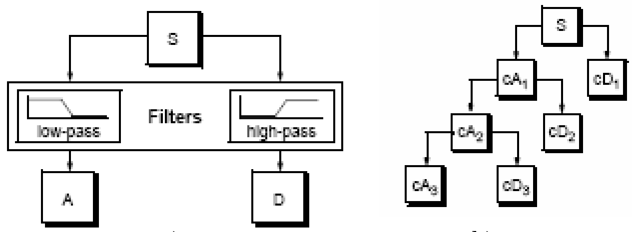
$$W(a,b)=\int_{-\infty}^{+\infty} f(t).\psi\left(\frac{t-b}{a}\right).dt \qquad (1)$$

Eq. 1 is known as Continuous Wavelet transform and it can be defined as the summation of multiplication of the existing signal with the scaled (a) and shifted (b) versions of the chosen wavelet function ψ. There are lots of wavelet functions like Haar,Daubechies etc. defined for wavelet transform.

Deviating from Eq. 1, in order to make operations on computers and digital processors discrete form of wavelet, Discrete Wavelet Transform (DWT) is used [9]. With this transform the signal is separated to coefficients called as approximations (cA) which carries low frequency components and coefficients called as details (cD) which carries high frequency components of the signal. This separation continues with the same operation applied to the low frequency components until the level which is required. The equations for the calculation of coefficients with DWT is given in Eq. 2 and Eq. 3 and a third order separation for a signal is shown in Fig. 4.

$$cA_j=\sum_{-\infty}^{+\infty} f(n).\phi_{j,k}(n)=\sum_{-\infty}^{+\infty} f(n).\frac{1}{\sqrt{2^j}}.\phi\left(\frac{n-k2^j}{2^j}\right) \qquad (2)$$

$$cD_j=\sum_{-\infty}^{+\infty} f(n).\psi_{j,k}(n)=\sum_{-\infty}^{+\infty} f(n).\frac{1}{\sqrt{2^j}}.\psi\left(\frac{n-k2^j}{2^j}\right) \qquad (3)$$



a) b)

Fig. 4 a)DWT b) 3 order separation with DWT

In Eq. 2, j is the order of separation and the function ϕ is the scaling function and it is related to the chosen wavelet transform.

cA and cD coefficients of DWT are interpreted to isolate faults from each other. Characteristics of the fault signals are always based on the high frequency components so just the cD coefficients are considered. This interpretation is done on-line as a result of a comparation with the rule base which is defined with the recorded observations of coefficients on fault signals. To prove robustness, rules on coefficients are defined as a comparation with upper and lower threshold values. A general demonstration of rule base is shown in Eq. 4.

If cD1>$Th\text{-}low_{cD1}$&cD1<$Th\text{-}high_{cD1}$&cD2>$Th\text{-}low_{cD2}$…
Then fault = f_1 (4)

The block diagram of generation of coefficients using DWT and isolation of faults with a decision logic block is shown in Fig. 5. One of the outputs of the rule base should define the normal operating condition of the system as healthy.

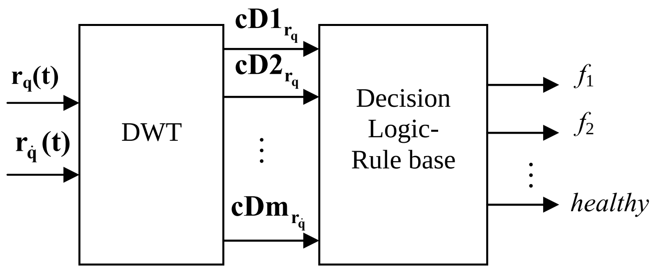


Fig. 5 Structure of fault isolation

IV. SIMULATION RESULTS

This section illustrates the proposed FDI system for robot manipulators with a simulation implemented under MATLAB. The manipulator for the simulation is a two-link planar manipulator under gravity. The dynamics of the manipulator and the generalized form are given in the following equations [10]:

$$\begin{bmatrix} (m_1+m_2)a_1^2+m_2a_2^2+2m_2a_1a_2\cos(\theta_2) & m_2a_2^2+m_2a_1a_2\cos(\theta_2) \\ m_2a_2^2+m_2a_1a_2\cos(\theta_2) & m_2a_2^2 \end{bmatrix}\begin{bmatrix}\ddot\theta_1\\ \ddot\theta_2\end{bmatrix} + \begin{bmatrix} -m_2a_1a_2(2\dot\theta_1\dot\theta_2+\dot\theta_2^2)\sin(\theta_2) \\ m_2a_1a_2\dot\theta_1^2\sin(\theta_2) \end{bmatrix} + \begin{bmatrix} (m_1+m_2)ga_1\cos(\theta_1)+m_2ga_2\cos(\theta_1+\theta_2) \\ m_2ga_2\cos(\theta_1+\theta_2) \end{bmatrix} = \begin{bmatrix}\tau_1\\ \tau_2\end{bmatrix} \qquad (5)$$

$$M(q)\ddot q+V(q,\dot q)+G(q)=\tau \qquad (6)$$

Here $M(q)$ is the inertia matrix, $V(q,\dot q)$ is the coriolis/centripedal vector and $G(q)$ is the gravity vector. The dynamics are calculated as the masses of links are at the end of the links, the manipulator moves under gravity, link masses are $m_1 = m_2 = 1$ kg., link lengths are $a_1 = a_2 =$ 1m and sampling frequency is 100 Hz..

As the robot control method the Computed Torque PID(CT-PID) control is used and defined as [10] :

$$\dot\varepsilon = e$$
$$\tau = M(q)(\ddot q_d + K_V\dot e + K_p e + K_i\varepsilon) + N(q,\dot q) \qquad (7)$$

The gains in Eq. 7 are chosen as $K_V = 100I_{2\times2}$, $K_p = 20I_{2\times2}$, $K_i = 500I_{2\times2}$.

For robot manipulators component faults(broken link, collision etc.), actuator faults(locked magnetic brake etc) and sensor faults(biases etc.) are defined in the literature. In this study just actuator faults are considered. Most studies are on locked joint and free-swinging joint faults and there are a limited number of studies on partial actuator faults. In this study these partial actuator faults are considered.

As the first step of the FDI system the Anfis structures are formed. For each link's position and velocity signals 4 independent Anfis are considered. With the structure shown in Fig. 3 the inputs are torques, previous sampling time instant position and velocity signals of each link as 6 inputs. For training 156 different trajectories with 76 samples are applied to M-Anfis. For each input two membership functions with gaussian bell shape is defined and hybrid learning method is considered. To show the robustness of the system time varying %5 uncertainty is added to robot dynamics. As a result with the model, the residuals are generated.

As the second step DWT is applied to the residuals for fault isolation. The number of samples for each DWT is 100 and this transform is performed with sliding window technique. daubechies1 is used as the wavelet function and for each residual the cD coefficients with fifth level are obtained.

As the last step the decision logic-rule base is obtained from simulation datas. In order not to increase the number of rules of rule base, just %50 and %30 faults for each actuator with three different trajectories are simulated and datas from these simulations are used for the rule definitions. Here it must be noted that the rules of rule base is obtained with these uncertainty added datas.

As an example of the system the trajectories for each link are given below and a %30 fault at link 1 at t = 20 is considered.

$$q_{d1}(t) = 1.\cos(t/2) \qquad (8)$$

$$q_{d2}(t) = 1.\sin(t/2)$$

$$q_1(0) = 0.1, q_2(0) = \dot{q}_1(0) = \dot{q}_2(0) = 0$$

The figures of the example is between 3-40s. 0-3 s. time interval is accepted as transient because of initial conditions and ignored. In Fig. 6 the time histories of paths, errors and applied torques of link 1,2 are shown. It can be seen that robot can continue operating with an acceptable error after fault. It is a talent of CT-PID.

In Fig. 7 position and velocity residuals of each link are shown. In pre-fault time interval the residuals are nearly zero. The time of fault detection can be thought as the significiant change in the residuals. Most FDI methods use fixed or adaptive residual thresholds for fault detection. It can be seen from Fig. 7 that the residuals are large enough for fault alarm but for intermittent faults it is hard to define time interval of fault because the residuals show periodic behaviour and all can decrease to zero at a time instant (t = 22 s. for r_1) It is hard for the system to detect and isolate partial small actuator faults because the system cannot decide if it is an uncertainty or fault. The simulation studies showed that the system cannot detect faults under %10 . In Fig. 8 the coefficients of residuals at fault isolation time are shown and the time instant for FDI is t = 20,36 s.

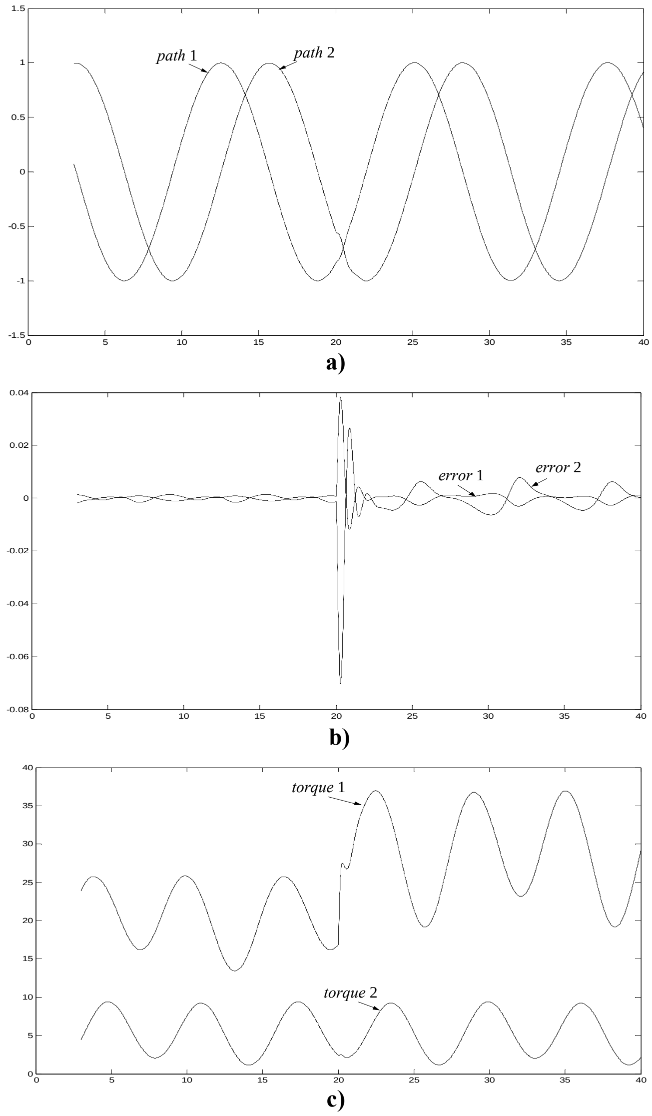


Fig. 6 Time histories of link 1,2
a) Paths **b)** Errors **c)** Applied torques

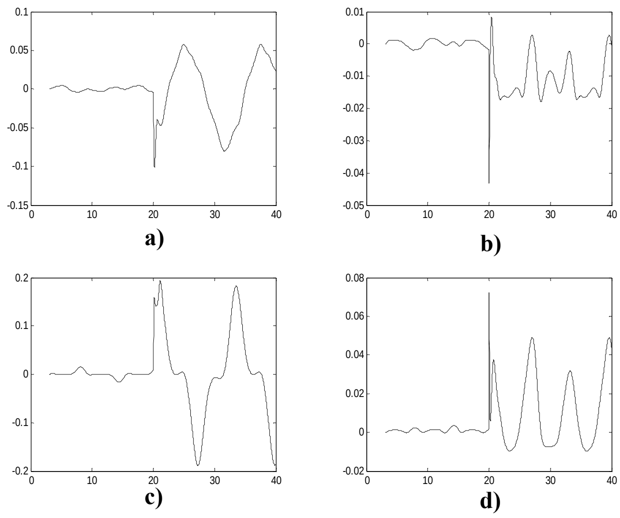
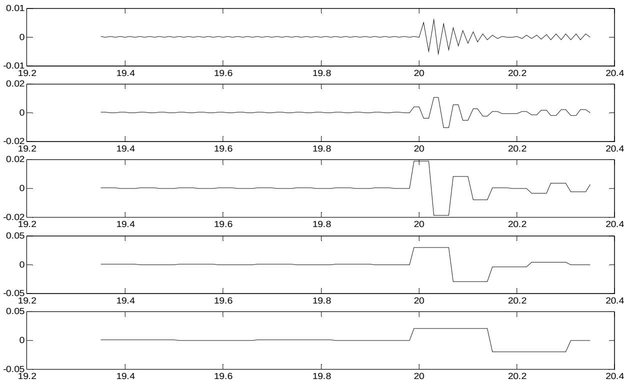
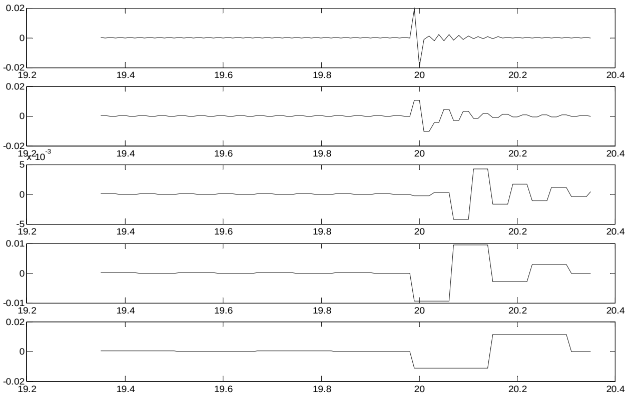


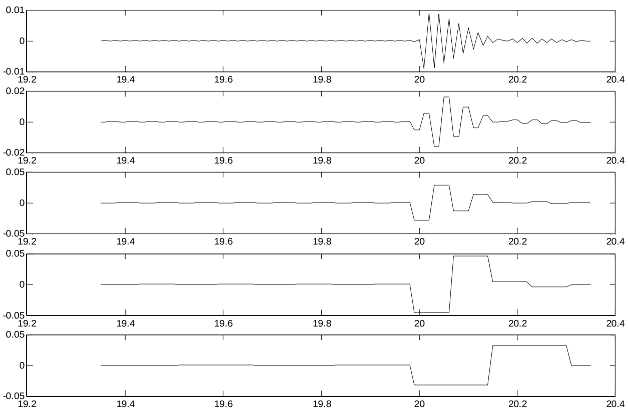
Fig. 7 Residuals **a)** Position residual of link 1(r_1)
b)Velocity residual of link 1(r_2)
c) Position residual of link 2(r_3)
d) Velocity residual of link 2(r_4)



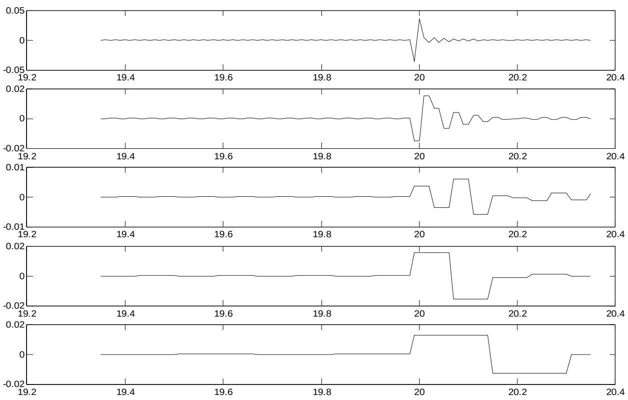
a)



b)



c)



d)

Fig. 8 Wavelet coefficients of residuals
a) Coefficients of r_1 **b)** Coefficients of r_2
c) Coefficients of r_3 **d)** Coefficients of r_4

V. CONCLUSIONS

In this study an FDI system robot manipulators is proposed. The system uses M-Anfis for robot modelling and residual generation and wavelets for fault isolation. The study is on actuator faults of manipulators and the next step will be the isolation of component and actuator faults.

The system's abilities are bounded with the number of rules and the rules have to be updated or calibrated for different uncertainties and new rules have to added for different partial faults.

Simulations studies showed that DWT as fault isolation part of the system are not fully capable of isolating all actuator faults. For the isolation part of the system other methods will be used in the future studies.

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