Fault Detection and Isolation for Manipulator Robot Using Optimal Unknown Input Observer

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Abstract: Fault detection and diagnosis is one of the important and challenging issues in the field of control engineering. The robotic mechanical systems used instead of human in industrial, unreachable and hazardous spaces are always exposed to different kinds of stress and are susceptible to different kinds of fault in their operators and sensors. Fault detection and diagnosis in shortest possible time after the occurrence of fault, fault isolation, and detection of faulty components may prevent serious damages and additional costs. This paper aims to detect and diagnose the faults of manipulator robot using unknown input observer. The proposed observer is able to estimate the virtual modes, generate proper residuals, diagnose and detect sensor faults, and make fault detection process robust respect to disturbance and noise. The challenge of this observer is to determine its parameters which are sometimes inconsistent with each other and therefore have to be determined in the order of priority based on fault detection goals. In this paper, we optimize and determine the parameters of unknown input observer using optimization genetic algorithm. The proposed observer combined with the comparative threshold designed in this paper minimizes the number of wrong alarms and fault detection failures. The simulation results and their comparison with the extended Kalman filter confirm the efficiency of the proposed observer in the robust fault detection and diagnosis for manipulator robot.

Keywords: Fault detection and isolation, manipulator robot, unknown input observer, genetic algorithm, adaptive threshold.

1. INTRODUCTION

The increased complexity of control systems in the recent years and their utilization in sensitive environments such as flight control, power plants, robotic industry, and chemical and nuclear processes has led to an ever-increasing use of fault detection systems. The occurrence of fault normally causes economic loss due to the reduced efficiency and failure of equipment. In worst possible conditions, the occurrence of fault may jeopardize the life of human beings. Fault detection and isolation (FDI) has recently attracted the attention of many researchers as there has been an ever-increasing demand for better efficiency combined with industrial safety. It is mentioned, the major challenges in fault detection and diagnosis are uncertainty, disturbance, and changeability of model in the course of time, which should be isolated from fault (Venkatasubramanian et al., 2003b). In other words, fault detection mechanism should be robust to uncertainty, disturbance, changes of model parameters, and noise.

In many methods of the fault detection and isolation area, the observer-based methods has attracted many interests (Frank et al., 1997). Unknown input observer is inherently robust to disturbance and uncertainty, provided that the system is observable and its parameters are properly determined (Hwang et al., 2010). The necessary and sufficient conditions are provided for the existence and design of input observer (Hammouri et al., 2010). The nonlinear unknown input observer design is investigated for fault detection in Lipschitz nonlinear systems (Chen et al., 2006). The sufficient condition of existence of nonlinear unknown input observer is achieved by linear matrix inequalities. The unknown input observer has been used for robust fault detection and diagnosis in chemical systems. The unknown input observer is used for robust fault detection in continuous stirred tank reactor (CSTR), (Zarei et al., 2013a, b). The simulation results confirm the efficiency of this method compared to the extended Kalman filter. In waste water treatment plant (WWTP), likewise, robust fault detection has been carried out by unknown input observer (Lafont et al., 2014). Since the model parameters of this system change with time, linearization of the model was performed around the balance point in each sampling and observer parameters were determined according to the obtained model for robust fault detection and diagnosis. The unknown input observer is used for nuclear reactors, according to relatively weak results of parameter estimation method in fault detection and diagnosis (Pang et al., 2014). The observer proposed in this paper has a structure similar to Kalman filter, but has an unknown input which also considers the issue of noise and random signals. The simulation results indicate the accuracy of this method in fault detection in the presence of Gaussian noises. In order a new method has also been proposed to simplify the design conditions for unknown input observer (Park, 2013). In this method, the system model is rewritten into two parts, with one part having poles located in origin which make observer design difficult. This isolation provides better conditions for designing the observer in the other part with non-origin poles. The unknown input observer is proposed for robust fault detection and diagnosis for three tanks system (Sobhani et al., 2012). The equations of this system are linearized and discretized in the course of time. In this paper, we focus on generation of structured residuals for the detection of sensor fault.

A robust unknown input observer is proposed for actuator fault detection in linear time-varying systems with persistence of disturbances (Li et al., 2017). The linear matrix inequalities and linear matrix equalities are used to calculate the observer parameters. The simulation results on a wind turbine show good performance of the proposed observer.

An unknown input observer-based decentralized fault detection and isolation is proposed for a class of large-scale interconnected nonlinear systems (Abassi et al., 2016). Also, this approach is improved (Abassi et al., 2017). In this method a bank of decentralized nonlinear input observer is used to detect actuator faults. The innovation of this approach is designing separately a nonlinear unknown input observer for each of the interconnected subsystems. On the other words, by using this approach there is no need to communicate with other subsystems for local UIO design. The stability theorem is given based on Lyapunov stability theorem driven by linear matrix equalities. The efficiency of this approach is shown by simulating on an automated highway as a large-scale interconnected nonlinear system.

The fault detection method is presented for high-order multi-agent systems based on unknown input observer (Liu et al., 2015). The simulation result on multi-agent system with five agents show good performance of the proposed observer with considering disturbances. The robust fault detection for leader-follower linear multi-agent systems is presented using robust unknown input observer (Zheng et al., 2017). The efficiency of the proposed observer for sensor and actuator fault detection and isolation is shown by simulation results.

The unknown input observer is used to detect and isolate actuator fault in five tank system (Tahraoui et al., 2016). A bank consist of two unknown input observers is designed for detection of two actuator faults using the dedicated residual signals. The performance of this approach is shown by simulation results.

Fault tolerant control (FTC) scheme is proposed based on H_∞ as a robust method (Belkhiat et al., 2015). In this approach a bank of generalized switched observer consist of three observers is designed to detect sensor fault with presence of unknown bounded disturbances. In this paper a compromise between the robustness and the detection of sensor fault is achieved. The feasibility of this approach is guaranteed by linear matrix inequality formulation.

Several methods have been proposed for fault detection and diagnosis in manipulator robots. A method for a 2-DOF manipulator robot is proposed based on prediction error in the presence of parameter uncertainties, without any need to measure robot joint acceleration (Dixon et al., 2000). A challenge in fault detection is the alternate fault detection mode (Sedighi et al., 2013). In this mode, system model continuously switches between faulty and faultless models. This paper attempts to diagnose alternate sensor fault in a manipulator robot with two degrees of freedom using the extended Kalman filter. The proposed method only diagnoses, but not detects, the fault. The actuators fault detection method is presented for a flexible joint robot (Yoo, 2012). In this method, tracking error signal is treated as residual and the fault is detected using statistical methods. In this paper, uncertainties in robot model have also been taken into consideration. The sensor fault detection and isolation method is proposed for a manipulator robot arm with six degrees of freedom using radial basis function (RBF) neural networks and linear matrix inequality (LMI), (Paviglianiti et al., 2010). A bank of the state observers is proposed to form the residual signal. RBF neural networks have been used to diagnose sensor fault in PUMA manipulator robot and have been implemented in practice (Eski et al., 2011).

In this paper, we diagnose and detect the faults of manipulator robot in a robust manner using a combination of unknown input observer and genetic algorithm, which have not yet been used for this type of robots and which is the innovation of this paper. In many of the methods proposed so far, there has not been a high percentage of fault isolation from disturbance, which has led to improper fault detection and wrong alarms. Unknown input observer is robust and increases the percentage of proper fault detection. The main goals of the UIO for fault detection and diagnosis are as follows:

- Stable state estimation.

- Robustness to the variation of the input signal.

- Robustness to the variation of the state signals.

- Robustness to the disturbance signals.

- Sensitivity of each residual only to own fault and robustness to the other faults.

However, there are some challenges in the implementation of this observer and in the computation of its parameters. One of these challenges is the impossibility of the implementation of all observer conditions and fault detection goals in a simultaneous way. Another challenge is the unequal number of equations and unknowns (i.e. observer parameters). In this paper, we determine the optimal parameters of unknown input observer using genetic algorithm, which significantly increases the percentage of isolation between fault and disturbance according to prioritization of fault detection goals. Therefore, determining the optimal observer parameters using genetic algorithm and adaptive threshold design for the residual signal guarantees the resistance of fault detection and diagnosis method. The comparison between the results generated by the combination of unknown input observer and genetic algorithm and the results produced by the extended Kalman filter reveals the robust and rapid performance of the proposed method in fault detection and diagnosis.

Different parts of this paper are organized as follows. Part 1 sets forth the manipulator robot equations. Part 3 reviews the process of designing the unknown input observer and determining its parameters using the genetic algorithm. Part 4 explains the process of designing the adaptive threshold. Part 5 analyses the simulation results and compares them with the extended Kalman filter. The final part presents the conclusion.

2. MANIPULATOR ROBOT DYNAMIC

For the purpose of this paper, we use a manipulator robot with two degrees of freedom as shown in Fig. 1. Below is the dynamic equation of this robot (Paviglianiti et al., 2010):

$$M(q)\ddot{q} + C(q,\dot{q}) = \tau \tag{1}$$

where, $q_{2\times1}$ is joints angle vector, $\dot{q}_{2\times1}$ is joints angular velocity, $\ddot{q}_{2\times1}$ is joints angular acceleration, and τ is joints torque vector. The matrices $M_{2\times2}, C_{2\times1}$ are mass, decentralized forces, and friction matrices respectively, which are obtained as indicated in Fig. 2. The robot parameters are contained in table 1 (Paviglianiti et al., 2010).

$$\begin{gathered} M(q) = \begin{bmatrix} p_1 + 2p_3\cos(q_2) & p_2 + p_3\cos(q_2) \\ p_2 + p_3\cos(q_2) & p_2 \end{bmatrix} \\ C(q,\dot{q}) = \begin{bmatrix} -p_3\sin(q_2)\dot{q}_1\dot{q}_2 - p_3\sin(q_2)(\dot{q}_1+\dot{q}_2)\dot{q}_2 \\ +f_{d1}\dot{q}_1 + f_{s1}\,\mathrm{sgn}(\dot{q}_1) \\ p_3\sin(q_2)\dot{q}_1^2 + f_{d2}\dot{q}_2 + f_{s2}\,\mathrm{sgn}(\dot{q}_2) \end{bmatrix} \end{gathered} \tag{2}$$

Angular acceleration of the joints is obtained by equation 3:

$$\ddot{q} = M^{-1}(q)\left(-C(q,\dot{q}) + \tau\right) \tag{3}$$

Considering the state vector as $x = [q_1 \quad q_2 \quad \dot{q}_1 \quad \dot{q}_2]^T$ and input vector as $u = [\tau_1 \quad \tau_2]^T$, robot mode equation is written according to (4):

$$\dot{x} = f(x,\tau) = \begin{bmatrix} x_3 \\ x_4 \\ M^{-1}(-C+\tau) \end{bmatrix} \tag{4}$$

2.1 Robot Dynamic Linearization

Since linear and discrete equations of the system are needed for designing the unknown input observer, we linearized and discretized the equations around the balance point using Jacobin method. Linearization of the equations needs balance point, which is obtained from $\dot{x} = f(x,0) = 0$. By solving this equation, the balance point was computed as $x_e = 0_{4\times1}$. By using Jacobin, the linear equation of the robot was obtained from (5):

$$\dot{x}(t) = A_c x(t) + B_c u(t) \tag{5}$$

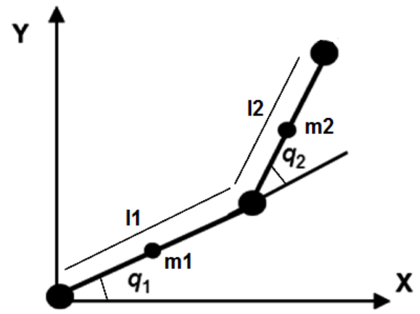

Fig. 1. 2-DOF manipulator robot arm.

Table 1. Robot parameters

Parameter	$p_1(kgm^2)$	$p_2 kgm^2)$	$p_3 kgm^2)$	
Value	3.473	0.193	0.242	
Parameter	$f_{d1}(Nm.s)$	$f_{d2}(Nm.s)$	$f_{s1}(Nm)$	$f_{s2}(Nm)$
Value	1.3	0.88	1.519	0.932

Table 2. Parameters of PID controllers

Parameter	K_{p1}	K_{d1}	K_{i1}
Value	100	25	5
Parameter	K_{p2}	K_{d2}	K_{i2}
Value	80	20	5

where, system and input matrixes are obtained from (6)

$$\begin{gathered} A_c = \left.\frac{\partial f}{\partial x}\right|_{x=x_e} = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \cdots & \frac{\partial f_1}{\partial x_4} \\ \vdots & \ddots & \vdots \\ \frac{\partial f_4}{\partial x_1} & \cdots & \frac{\partial f_4}{\partial x_4} \end{bmatrix} \\ = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & -0.4367 & 0.6630 \\ 0 & 0 & 0.9844 & -6.0615 \end{bmatrix} \\ B_c = \left.\frac{\partial f}{\partial u}\right|_{x=x_e} = \begin{bmatrix} \frac{\partial f_1}{\partial u_1} & \frac{\partial f_1}{\partial u_2} \\ \vdots & \vdots \\ \frac{\partial f_4}{\partial u_1} & \frac{\partial f_4}{\partial u_2} \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0.3360 & -0.7572 \\ -0.7572 & 6.8880 \end{bmatrix} \end{gathered} \tag{6}$$

If sampling rate is sufficiently small, the approximate (7) can be used to discretize (5):

$$\dot{x}(t) \cong \frac{x(t+\Delta t) - x(t)}{\Delta t} \tag{7}$$

Therefore, the discrete equation will be according to (8):

$$\begin{gathered} x(t+\Delta t) \cong \dot{x}(t)\Delta t + x(t) \rightarrow \\ x(k+1) = (A_c\Delta t + I)x(k) + B_c\Delta t u(k), k = 0,1,2,\ldots \end{gathered} \tag{8}$$

By considering $\Delta t = 0.01$, the discrete equation of the robot is rewritten according to (9):

$$
\begin{aligned}
& x(k+1) = Ax(k) + Bu(k) \\
& y(k) = Cx(k) \\
& A = A_c \Delta t + I = \begin{bmatrix} 1 & 0 & 0.01 & 0 \\ 0 & 1 & 0 & 0.01 \\ 0 & 0 & 0.995633 & 0.006630 \\ 0 & 0 & 0.009844 & 0.939385 \end{bmatrix} \\
& B = B_c \Delta t = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0.003360 & -0.007572 \\ -0.007572 & 0.068880 \end{bmatrix} \\
& C = I_{4\times4}
\end{aligned} \tag{9}
$$

In order to control the joints angle of the robot, we used two PID controllers to track the reference route as $q_d(t) = 1.5\sin(1.75t)$ (Paviglianiti et al., 2010). Table 2 represents the parameters of these controllers which have been obtained by Ziegler-Nichols method.

3. UNKNOWN INPUT OBSERVER DESIGN

In fault detection and diagnosis methods based on unknown input observer, disturbance is considered as the unknown input. The main goal of designing this type of observer is to isolate the disturbance from the residual signal. To design the unknown input observer, mode and output equations of the discrete system are obtained from equation 10 (Zarei et al., 2014):

$$
\begin{cases} x(k+1) = Ax(k) + Bu(k) + B_f f(k) + B_d d(k) \\ y(k) = Cx(k) + D_f f(k) + D_d d(k) \end{cases} \tag{10}
$$

where, $x_{n\times1}$ is state vector, $u_{m\times1}, y_{l\times1}$ are input and output vectors of the system, $f_{r\times1}$ is fault vector, and $d_{j\times1}$ is disturbance vector. $A_{n\times n}, B_{n\times m}, C_{l\times n}$ are system matrix, input matrix and output matrix respectively. $B_{fn\times r}, D_{fl\times r}, B_{dn\times j}, D_{dl\times j}$ are fault and disturbance matrixes in mode and output equations.

With these definitions, model and residual estimation equations of the observer will be according to (11):

$$
\begin{aligned} & z(k+1) = Fz(k) + Gy(k) + Ju(k) \\ & r(k) = L_1 z(k) + L_2 y(k) \end{aligned} \tag{11}
$$

where, $z_{n\times1}$ is the state vector that is estimated by UIO observer, $r_{n\times1}$ is residual signal vector, $F_{n\times n}, G_{n\times l}, J_{n\times m}, L_{1n\times n}, L_{2n\times l}$ and are design matrixes. The state estimation error vector is defined as (12):

$$
e(k) = z(k) - Tx(k) \tag{12}
$$

where, $e_{n\times1}$ is the estimation error vector and $T_{n\times n}$ is design matrix. With this definition, fault dynamic computation will be as follows:

$$
\begin{aligned} e(k+1) &= z(k+1) - Tx(k+1) = Fz(k) + Gy(k) + Ju(k) \\ &\quad - T\left(Ax(k) + Bu(k) + B_f f(k) + B_d d(k)\right) \\ &= Fz(k) + (GC - TA)x(k) + (J - TB)u(k) \\ &\quad + (GD_f - TB_f)f(k) + (GD_d - TB_d)d(k) \end{aligned} \tag{13}
$$

By replacing $z(k) = e(k) + Tx(k)$ in (13), the estimation error dynamic of the unknown input observer is obtained from (14):

$$
\begin{aligned} e(k+1) &= Fe(k) + (GC - TA + FT)x(k) + (J - TB)u(k) \\ &\quad + (GD_f - TB_f)f(k) + (GD_d - TB_d)d(k) \end{aligned} \tag{14}
$$

The residual signal is written as (15) by replacing the output equation and in (11):

$$
\begin{aligned} r(k) &= L_1 z(k) + L_2\left(Cx(k) + D_f f(k) + D_d d(k)\right) \\ &= L_1 e(k) + (L_1 T + L_2 C)x(k) + L_2 D_f f(k) + L_2 D_d d(k) \end{aligned} \tag{15}
$$

After computing the observer error dynamic, we determined its parameters to achieve fault detection and diagnosis goals. The goals of designing the unknown input observer for fault detection and diagnosis are as follows:

1. Estimation error dynamic of the observer should be stable.

2. Change of system input signal should not take any impact on the residual signal, fault dynamic, and fault detection.

3. The value of system modes should not affect error dynamic (18) and residual signal (19).

4. The impact of disturbance on error dynamic (20) and residual signal (21) should be eliminated.

5. The impact of faults on error dynamic (22) and residual signal (23) should be maintained and each residual and error should be dependent only on its corresponding fault so that the faults can be identified and isolated from each other. In order to achieve the above mentioned goals, equations 16-23 should be established.

$$F \text{ is Horwitz} \tag{16}$$

$$J - TB = 0 \tag{17}$$

$$GC - TA + FT = 0 \tag{18}$$

$$L_2 C + L_1 T = 0 \tag{19}$$

$$GD_d - TB_d = 0 \tag{20}$$

$$L_2 D_d = 0 \tag{21}$$

$$GD_f - TB_f \neq 0 \tag{22}$$

$$L_2 D_f \neq 0 \tag{23}$$

3.1 Genetic Algorithm

There will always be some challenges in the establishment of observer conditions and (16) to (23). The first challenge is the unequal number of equations and the number of unknowns. The second challenge is that the simultaneous implementation of all the above conditions is not feasible in many systems and equations may be inconsistent with each other (Hammouri et al., 2010). Therefore, the above mentioned goals should be arranged in the order of priority. In this paper, we use genetic algorithm to optimize a fitness function based on the priority of each equation so that optimal observer parameters are obtained. The genetic algorithm uses Darwin's natural selection principles to find an optimal formula for prediction or adaptation of the pattern. Genetic algorithm starts from a set of initial random solutions named population. Each component of the population, called chromosome, represents a problem answer. Chromosomes are transformed in successful repetitions called generation. In each generation, chromosomes are evaluated by computing the fitness function. To create the next generation, the new chromosomes, which are called children, are developed by one of two actuators of displacement and mutation. The new generation is formed based on the value of fitness function of the parents and children or deletion of others in order to keep the population fixed. After several generations, the algorithm is conducted towards the best chromosome which, in ideal mode, provides an optimal answer to the problem (George et al., 2013). Normally, the initial selection is made randomly. In random sampling, the number of chromosomes is determined based on the probability of survival of that chromosome. Diagram block of genetic algorithm is shown in Fig. 2. Equation (24) represents the fitness function used for optimal computation of unknown input observer parameters:

$$\begin{aligned} J_{fit} = & w_1 \left(\left|\mathrm{eig}(F)\right| - 0.5\right)^T \left(\left|\mathrm{eig}(F)\right| - 0.5\right) \\ & + w_2 (GC - TA + FT)^T (GC - TA + FT) \\ & + w_3 (L_2C + L_1T)^T (L_2C + L_1T) \\ & + w_4 (GD_d - TB_d)^T (GD_d - TB_d) \\ & + w_5 (L_2D_d)^T (L_2D_d) \\ & + w_6 (GD_f - TB_f - I)^T (GD_f - TB_f - I) \\ & + w_7 (L_2D_f - I)^T (L_2D_f - I) \end{aligned} \tag{24}$$

Where, $w_i, i = 1:7$ are weighting parameters of the fitness function sentences and $\mathrm{eig}(.)$ is the eigenvalue. In determining the observer parameters, the first priority is always the stability of observer. The next priority is the presence of faults in residuals so that all faults can be detected (Hammouri et al., 2010). For the purpose of full isolation of the faults from each other, (22) and (23) are considered in polar form so that each residual is dependent on its corresponding fault. The omission of effect of disturbance and modes on the residual and error are the next priorities. Based on these priorities, the values of weighting parameters are represented in table 3. The initial values have been randomly selected.

4. ADAPTIVE THRESHOLD

After generating the residual signal, it is time to set the threshold and make decision for fault detection. Threshold is a curve which is depicted on the residual signal in normal and fault-free mode in such a way that the residual is placed inside the threshold. In the time of fault occurrence, if fault detection method is efficient, the residual signal exits the threshold and the fault alarm is activated.

$$\begin{cases} |r(t)| < \text{Threshold}, & \text{for fault-free case} \\ |r(t)| \geq \text{Threshold}, & \text{for faulty case} \end{cases} \tag{25}$$

So far, many methods have been used for making decision on the residual signal. From among these methods, adaptive threshold is an efficient method for fault detection. To determine the fixed threshold, it is assumed that the residual has normal distribution with mean m and variance ν. By using normal distribution formula, we can use the corresponding time of t_β and mean and variance to have the probability β on the residual signal (Sobhani et al., 2012).

$$\beta = \mathrm{P}\left(\left|\frac{r(t) - m}{\nu}\right| < t_\beta\right) \tag{26}$$

Table 3. Weighting parameters of fitness function

Parameter	w_1	w_2	w_3	w_4
Value	1	0.4	0.4	0.7
Parameter	w_5	w_6	w_7	
Value	0.7	1	1	

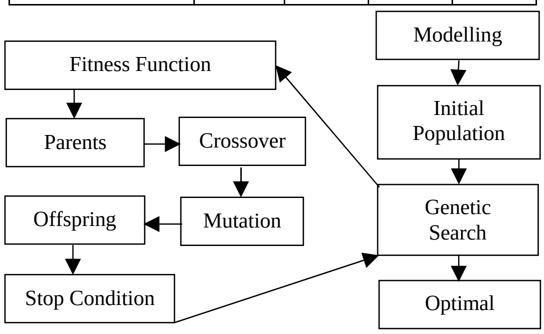

Fig. 2. Block diagram of genetic algorithm.

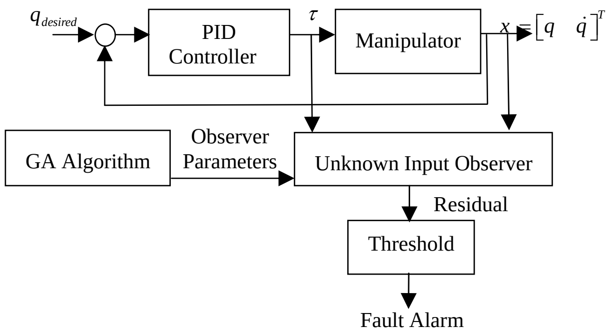

Fig. 3. Block diagram of proposed method.

Based on this description, the fixed threshold (positive sign of up threshold and negative sign of down threshold) can be obtained from (27):

$$T = m \pm t_\beta v \tag{27}$$

where, T is the fixed threshold and $t_\beta = 1,2,3$. The bigger t_β, the bigger the value of the fixed threshold and the bigger the probability of non-detection of the faults with smaller rang. On the other hand, the smaller t_β, the smaller the value of the fixed threshold and the bigger the number of wrong alarms. Therefore, the fixed threshold cannot guarantee a high percentage of proper fault detection. But this problems can be solved by making a change in the equation and converting it to a comparative equation. In this method, mean and variance of the residual signal data along a specific window is used to generate the threshold on the residual signal. Moreover, a weighting parameter is used to prioritize the recent data or soften the threshold. The adaptive threshold is obtained by (28) (Sobhani et al., 2012).

$$T(t) = \bar{m}(t) \pm t_\beta \bar{v}(t) \tag{28}$$

where, $\bar{m}, \bar{v}$ and are mean and variance along the window with weighting parameter, which are obtained by (29):

$$\begin{aligned} \bar{m}(t) &= \xi m(t) + (1-\xi) m(t-1) \\ \bar{v}(t) &= \xi v(t) + (1-\xi) v(t-1) \end{aligned} \tag{29}$$

Where, $m(t)$ and $v(t)$ are mean and variance along the window and $\xi \in (0,1)$ is the weighting parameter. It should be noted that the longer the window or the bigger the number of data located in the window, the softer the threshold will be and the more it will proceed towards the threshold. On the other hand, the smaller the length of window, the more the threshold will change and, in other words, the more it tracks the noise. Given that noise is a random signal, a compromise should be made between these two components by selecting a proper window length. Figure 3 illustrates the diagram block of the proposed method.

5. SIMULATION RESULTS

In order to simulate the unknown input observer for detection and diagnosis of manipulator robot fault, four faults were set in robot sensors and two disturbances were set in the first and second joints. Therefore, fault and disturbance matrixes are according to (30). The time of occurrence and the range of faults and disturbances are contained in table 4, 5 and Fig. 4.

$$\begin{aligned} B_f &= 0_{4\times4} \\ D_f &= I_{4\times4} \\ B_d &= \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}^T \\ D_d &= 0_{4\times2} \end{aligned} \tag{30}$$

Considering the fitness function in genetic algorithm in (24), observer design matrixes are as follows:

$$F = \begin{bmatrix} 0.5 & 1 & 0 & 0 \\ 0 & 0.5 & 1 & 0 \\ 0 & 0 & 0.5 & 1 \\ 0 & 0 & 0 & 0.5 \end{bmatrix}$$

$$T = \begin{bmatrix} 0 & 0 & 0.3491 & 0.4612 \\ 0 & 0 & 0.3122 & 0.3933 \\ 0 & 0 & 0.2012 & 0.4016 \\ 0 & 0 & 0.0032 & 0.0341 \end{bmatrix}$$

$$L_1 = \begin{bmatrix} 1 & 0 & -1.9213 & -2.8212 \\ -0.9821 & 1 & 0 & 0.5101 \\ 7.0128 & -7.7824 & 1 & 0 \\ 0 & -1.8205 & 1.9277 & 1 \end{bmatrix}$$

$$J = \begin{bmatrix} -0.002319 & -0.001929 & -0.002364 & -0.0000247 \\ 0.029124 & 0.024726 & 0.026138 & 0.002324 \end{bmatrix}^T$$

$$G = I_{4\times4}$$

$$L_2 = I_{4\times4}$$

The measurement noise variance in sensors is 0.01, the number of data of each window for the adaptive threshold is 100, and the weighting parameters is $\xi = 0.8$.

To determine the threshold in fault-free mode, the simulation is performed and the up and down thresholds are computed by (29). Next, the faults are applied to the manipulator robot and the simulation is performed again. Fig. 5 to Fig. 8 illustrate the residuals. As you can see, each residual is only dependent on its corresponding fault. In the time of fault occurrence, the corresponding residual signal exits the threshold and the alarm is activated. Based on the results, in addition to detecting the occurrence of all faults, the type of fault can also be detected and the allocated alarm can be notified to user. Furthermore, none of the residuals is sensitive to disturbance and there will be no wrong alarm due to the presence of disturbance. According to the results, the number of wrong alarms reaches zero, which indicates the resistance of the proposed observer to disturbance.

5.1 Comparison Result with Kalman Filter

In this part, we compare the proposed method with the extended Kalman filter to confirm the efficiency of the proposed observer. The extended Kalman filter is one of the most widely used observers for mode estimation and fault detection in non-linear systems which uses Jacobin linearization technique around the previous estimated point. In this filter, the covariance of estimation error and the modes of the next moment are estimated through two steps of time updating and measurement. For the purpose of fault detection and diagnosis, the difference between actual modes of the robot and the estimated modes are used as the residual signal (Axelsson et al., 2010). Fig. 9 to Fig. 12 illustrate the estimation error (residuals) which are generated by the extended Kalman filter. As you can see in the figures, the residuals are sensitive to both disturbances in addition to faults. In effect, each residual treats each disturbance as a fault, which was expectable due to lack of resistance in this filter. Moreover, not all the residuals are only dependent on their corresponding faults. According to the figure, only the residual 2 is dependent on fault 2. The residuals 1 and 3 are dependent on both faults 1 and 3 and the residual 4 is dependent on two faults 2 and 4. Therefore, the fault 2 can be detected from residual 2. Then, fault 4 can be detected from the residual 4 and omission of fault 2. But the faults 1 and 3 are not isolatable because both residuals 1 and 3 have reacted to both faults. The extended Kalman filter not only fails to isolate the faults 1 and 3 but also treats all disturbances as fault, which results in the increased wrong alarms. Therefore, the comparison between the proposed observer and the extended Kalman filter confirms the efficiency of the unknown input observer.

Table 4. Specification of faults

Fault	f_1(rad)	f_2(rad)	f_3(rad/s)	f_4(rad/s)
Magnitude	0.2	0.1	0.25	0.35
Start time	15	35	70	75

Table 5. Specification of disturbances

Disturbance	d_1(rad)	d_2(rad)
Magnitude	0.4	0.5
Start time	10	50
Stop time	20	60

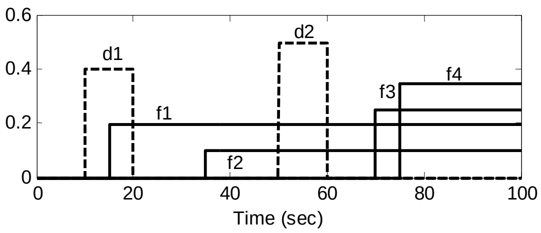

Fig. 4. Faults and disturbances.

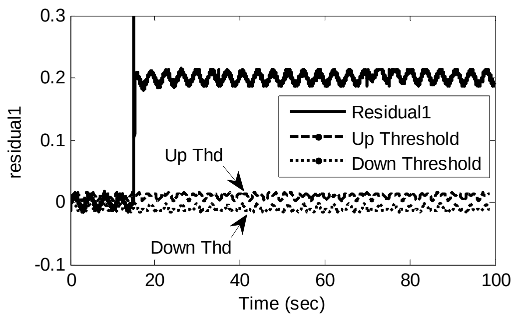

Fig. 5. Residual 1 generated by the proposed UIO.

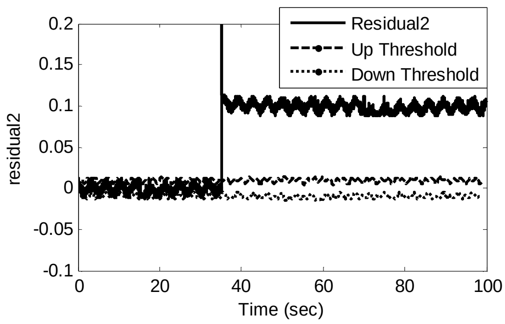

Fig. 6. Residual 2 generated by the proposed UIO.

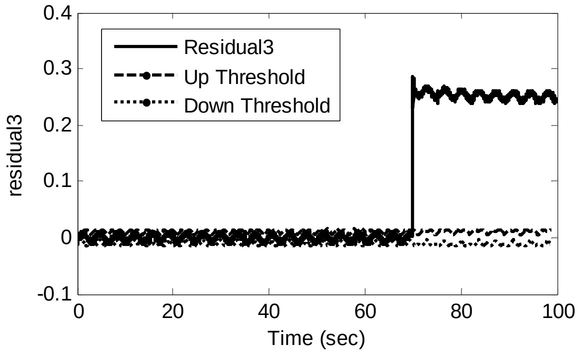

Fig. 7. Residual 3 generated by the proposed UIO.

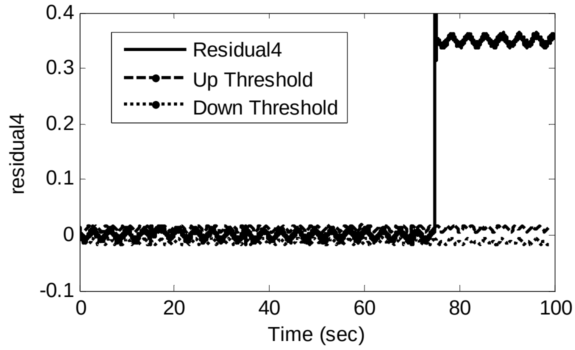

Fig. 8. Residual 4 generated by the proposed UIO.

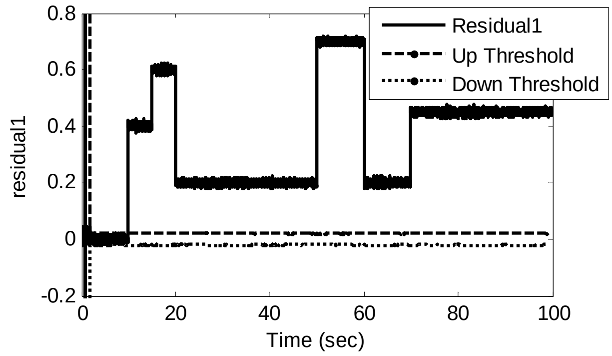

Fig. 9. Residual 1 generated by EKF.

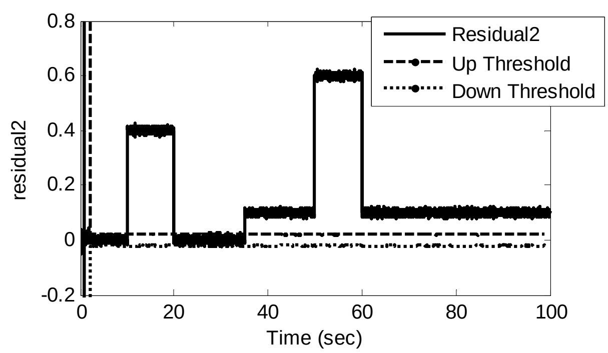

Fig. 10. Residual 2 generated by EKF.

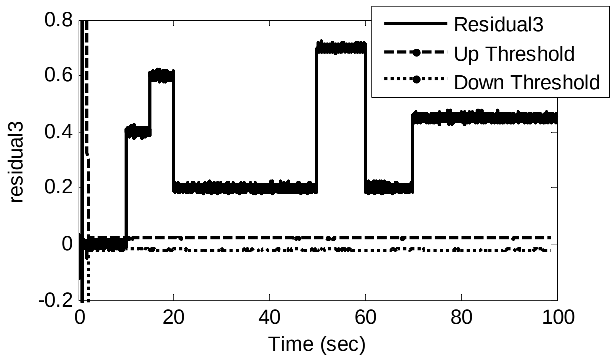

Fig. 11. Residual 3 generated by EKF.

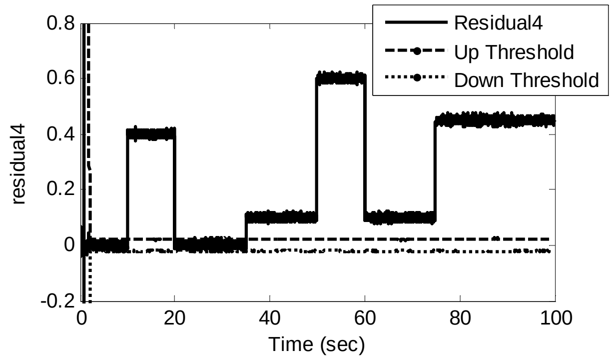

Fig. 12. Residual 4 generated by EKF.

5. CONCLUSION

In this paper, we designed an unknown input observer for fault detection and diagnosis in manipulator robot. The most important goal of using this observer is to make the residual signal robust respect to disturbance. There are two major challenges in designing this observer and computing its parameters. The first challenge is the unequal number of equations and unknowns. The second challenge is the impossibility of establishment of all equations and the presence of inconsistency. In order to overcome these two challenges, we used genetic algorithm to find optimal parameters and prioritize the equations and the goals of fault detection and diagnosis. As shown in simulation results, the proposed observer combined with the adaptive threshold is able to detect the occurrence of all faults. Furthermore, by determining the appropriate observer parameters, the residual is only dependent on its corresponding fault. Therefore, the type of fault can also be identified in addition to the occurrence of fault. Considering the goal of using this observer and determining the optimal parameters, the residuals are robust respect to disturbance and no disturbance is wrongly treated as fault.

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