Design of Fault Tolerant Flight Control System

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Abstract: - The purpose of the paper is to present an approach to detect, isolate and accommodate the sensor or actuator faults using bank of observer and unknown input observers (UIO). Full order observers, reduced order observers, unknown input observers and Kalman Filter are widely used in state estimations [1]. After the estimation of states, fault detection and isolation can be provided by conducting residual analysis. Despite the existence of unknown inputs, fault detection and isolation is implemented for a very large, four-engined, cargo jet aircraft model. Sensor accommodation is realized via switching under redundant sensor existence assumption. Actuator accommodation is provided by gain scheduling. Hence, if a fault occurs in an actuator corresponding to the control surfaces, the remainder (n-1) actuators are used to avoid hazardous flight regime. Sensor or actuator faults are detected by using residuals. Sensor faults are effective on the outputs while actuator faults are effective on the state equations. Fault isolation is implemented by taking into account that each residual is sensitive to all of the other faults but one fault. Fault detection, isolation and accommodation are shown to be functional through the simulations.

Key-Words: - Fault detection, isolation, accommodation, fault tolerant flight control, observer and unknown input observers

1 Introduction

Hajiyev and Caliskan designed a Kalman filter for the effects of the sensor and actuator faults in the innovation process, and used a decision approach to isolate the sensor and actuator faults. The presented reconfigurable control algorithm is based on the Extended Kalman Filter (EKF). Reconfiguration procedure is executed by considering the identified control distribution matrix. In the simulations, the longitudinal dynamics of an aircraft control system are considered, and control reconfiguration is examined. The principal block diagram of a fault tolerant aircraft control system is offered [2].

Soloway and Haley reported the preliminary results from the research being conducted in reconfigurable flight control. It highlights the Neural Generalized Predictive Control algorithm, which is capable of real-time control law reconfiguration, model adaptation, and the ability to identify failures in control effectiveness. It also presents results for a commercial transport aircraft simulation where the elevator is frozen during the flight and the algorithm reconfigures to use symmetric aileron deflections to control pitch rate, thereby stabilizing the aircraft [3].

Ostroff and Bacon used an improved control allocator that minimizes both effector rate and position, utilizing a multi-pass strategy to restore lost control power due to saturation using the remaining unsaturated controls. Command model flying parameters are adaptively manipulated online to comply with reduced levels of control power further reducing saturation. A classically designed compensator placed around each actuator underpins strategy to reduce jitter due to sensor noise in the control variable responses while preserving decoupling of original control. Improvements due to these modifications are demonstrated on an advanced tailless fighter [4].

Hajiyev and Caliskan covered the combined fault diagnosis and reconfiguration in flight control systems [1].

Caliskan presented a Neural Network identification of icing parameters in an A340 aircraft and a reconfiguration technique to keep the aircraft performance close to the performance prior to icing. The off-line training for identifying the clear and iced dynamics was based on the Levenberg-Marquard Backpropagation algorithm [5].

Perez et al presented a fault tolerant control application using neural networks-based compensation schemes. The design consists of supervising the process possible faults using an observer that allows determining the present fault and its direction and then it will be used a classification neural network which will activate the appropriate controller according to the identified fault type. In this work the superior tank water level was controlled [6].

Iqbal et al developed a linear model based FDI framework of nonlinear three-tank system. The nonlinear model was analytically linearized using perturbation theory. Simulations were carried out to verify the linearization and effectiveness of the proposed framework, for fault detection, isolation and estimation of abrupt, incipient in the presence of model uncertainties as well as for simultaneous multiple faults [7].

Mechiche and proposed to design a fault detection filter for a linear time invariant system using the non-dominated sorting genetic algorithm II. The fault detection filter was an observer with a set of projectors that map each fault in a specific residual direction. The design of the fault detection filter was formulated as a multiobjectives optimization problem in the frequency domain. The approach was demonstrated through the detection and the isolation of sensor and actuator faults for a linear aircraft model [8].

Acuna and Rios-Bolivar presented an approach for implementation of control system with anti-windup compensation using fault detection multifiltering. The residual signal used for anti-windup compensation was obtained from a filter bank for fault detection, thus it is not necessary its explicit measurement. This residual signal was considered as a fault, in order to design the fault detection filter. The filter bank was synthesized using robust LMI based control techniques. A numerical example to probe the proposed implementation method effectiveness was presented [9].

Wang et al presented the design of a lateral control system for a loitering aircraft of aileron-less folding wing. The paper focused on bank-to-turn by differential movement of elevators and skid-to-turn by rudder deflection. The flight path track loop was designed based on the self-organizing fuzzy control algorithm for the aircraft to fly in a desired path. They claimed the results show that the control plans are feasible and the control system is adequately robust to meet the requirements of the course control [10].

Vinatoru offered a methodology to use the results from a simulation on a laboratory installation to control and fault detection for the hydro power plants [11].

Romulus et al presented a new on-line parametric identification and discrete optimal command algorithm for mono or multivariable linear systems. The method performed to the automatic command of the flying objects' movement. They claimed that the simulation results obtained with good results, for identification and optimal command of an air-air rocket's movement in vertical plain regarding to target's line [12].

Canureci et al presented a methodology for using the results of a simulation on a laboratory installation in the level control in coupled tanks. They claimed that the research would be extended to also implement modeling algorithms and detection and localization of the possible faults types that appear in the plant [13].

Cruz-Victoria and Gonzalez-Sanchez proposed a controller designed using algebraic techniques for a DC motor. The failures were estimated trough a reduced order observer to reject their effect on the system. This paper represented the first phase in a Bond Graphs´ based approach to determine the diagnosability condition [14].

Romulus et al presented an algorithm for identification of the longitudinal and lateral movements of an aircraft. For identification a reduced order observer has been projected. With the obtained reduced order observer a stabilization compensator has been made. They claimed that the obtained results show that the algorithm may be used with good results to any system's identification [15].

Rao et al presented a variable structure based sliding mode controller for recovery of an aircraft from spin. The spin recovery problem was formulated as a two point boundary value problem. Using the bifurcation analysis results of the aircraft, the spin states of aircraft were identified. Once the aircraft enters into spin, the controller was activated to bring it back to a desired state which is a level flight trim solution also found from a bifurcation map of the aircraft model [16].

Faisal et al proposed a new technique to detect the occurrence of incipient fault and voltage disturbances. The technique was used the S-transform and the Support Vector Regression to extract features from the recorded voltage and currents waveforms and to detect the potential occurrences of incipient fault and voltage disturbance. A case study was presented to evaluate the accuracy of the S-transform based SVR in detecting incipient faults and voltage disturbances occurring in the power distribution networks [17].

Mihai et al presented an algorithm for identification of the longitudinal and lateral movements of an aircraft. For identification a prediction state observer (Luenberger observer) has been projected. With the obtained state observer a stabilization compensator has been made. They claimed that the presented Matlab program may be used with good results for identification and control of any system [18].

Rios-Bolivar et al analyzed the existing relations between the imprecise computation and the fault tolerant control [19].

In this study, first a Fault Detection and Isolation (FDI) based on the full-order UIO structure is presented. Then the accommodation technique is given.

In the FDI approach, extra design freedom is required for generating directional residuals in fault isolation [20]. The necessary and sufficient conditions for the UIO to exist are given.

In the paper, simulations are performed on the fourth-order dynamical model of an aircraft [21]. The nominal model of the aircraft is obtained under nominal flight regime; however, the parameters of the model are subject to variations under different flight conditions. The simulations illustrate that the proposed FDI scheme is capable of detecting and isolating the sensor or actuator failures in a variety of situations. The sensor or the actuator faults are correctly detected and isolated. Generalized Observer Scheme (GOS) is utilized to design each residual to be sensitive to faults in all but one of the sensors and actuators [22].

The approach presented in this paper can only isolate a single fault either in a sensor or in an actuator at the same time because the probability for occurring two or more faults at same time is very small in practice.

After the isolation of the faulty sensor, reconfiguration is provided by our approach. Sensor accommodation is realized via switching under redundant sensor existence assumption. Actuator accommodation is provided by gain scheduling. Hence, if a fault occurs in an actuator corresponding to the control surfaces, the remainder (n-1) actuators are used to avoid of hazardous flight. Accommodation effects are also shown thoroughly the simulations. All of the sensors and actuator accommodations are executed correctly as seeing the simulations by our switching or gain scheduling. Advantage of the accommodation technique is quite simple, feasible and improvable in comparison with most of the reconfiguration techniques.

2 Problem Formulation

The principle of the model based fault detection is depicted in Figure 1.

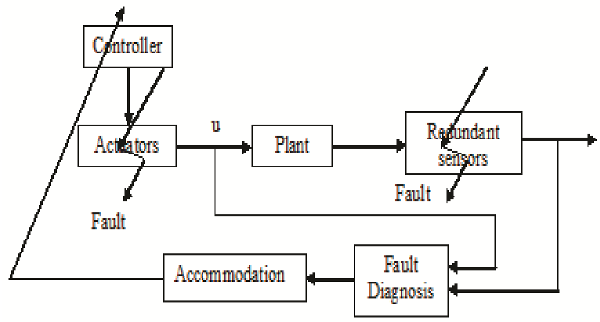

Figure 1 Scheme for the model based fault detection

A dynamic system whose state variables converge to the estimates of the state variables of another system is called an observer of the latter system [1].

In observers, two factors are most important: First, the model must be as accurate as possible, and secondly, the dynamics of the observer must be faster than dynamics of the plant itself [1].

2.1 Observers

Consider a continuous linear time invariant steady space model of the system:

$$\begin{aligned} \dot{x}(t) &= Ax(t) + Bu(t) \\ y(t) &= Cx(t) \end{aligned} \tag{1}$$

x represents the state vector, u represents input vector, y represents sensor output, A represents system coefficient matrix, B represents input coefficient matrix, C represents output coefficient matrix.

The structure of the observer is described as [1]:

$$\dot{z}(t) = Fz(t) + Gy(t) + Lu(t) \tag{2}$$

The error vector is given by:

$$e(t) = z(t) - Tx(t) \tag{3}$$

Using Equation (1) and (2), derivative of the error vector is obtained:

$$\dot{e}(t) = F(z(t) - Tx(t)) + (FT - TA + GC)x(t) + (L - TB)u(t) \tag{4}$$

Equations;

$$FT - TA + GC = 0 \tag{5}$$
$$L - TB = 0 \tag{6}$$

are satisfied, equation (4) can be written as:

$$\dot{e}(t) = Fe(t) \tag{7}$$

The solution of the Equation (7) is:

$$e(t) = e^{Ft} e(0) \tag{8}$$

If the matrix F is selected Hurwitz, the solution goes to zero asymptotically:

$$\lim_{t \to \infty} e(t) = 0 \tag{9}$$

and it follows:

$$\lim_{t \to \infty} z(t) = \lim_{t \to \infty} Tx(t) \tag{10}$$

2.2 Unknown Input Observers (UIO's) For Sensor and Actuator Faults

Consider a continuous linear time invariant steady space model of the system:

$$\begin{aligned} \dot{x}(t) &= Ax(t) + Bu(t) + Ed(t) \\ y(t) &= Cx(t) \end{aligned} \tag{11}$$

d and E represent the unknown input vector and the unknown input distribution matrix respectively.

The structure of the unknown input observer is described as [23]:

$$\begin{aligned} \dot{z}(t) &= Fz(t) + TBu(t) + Ky(t) \\ \hat{x}(t) &= z(t) + Hy(t) \end{aligned} \tag{12}$$

The error vector is given by:

$$e(t) = x(t) - \hat{x}(t) \tag{13}$$

Using Equation (11) and (12), derivative of the error vector is obtained:

$$\begin{aligned} \dot{e}(t) = {} & (A - HCA - K_1C)e(t) - \\ & [F - (A - HCA - K_1C)]z(t) - \\ & [K_2 - (A - HCA - K_1C)H]y(t) - \\ & [T - (I - HC)]Bu(t) - (I - HC)Ed(t) \end{aligned} \tag{14}$$

$\hat{x}$ represents the estimated state vector, and T, K and H are matrices satisfying requirements:

$$(HC - I)E = 0 \tag{15}$$
$$T = I - HC \tag{16}$$
$$F = A - HCA - K_1C \tag{17}$$
$$K_2 = FH \tag{18}$$
$$K = K_1 + K_2 \tag{19}$$

To design robust sensor fault isolation schemes, all actuators are assumed to be fault-free and the system equations can be expressed as below [22]:

$$\dot{x}(t) = Ax(t) + Bu(t) + Ed(t) \tag{20a}$$
$$y^j(t) = C^j x(t) + f_s^j \quad for\ j = 1, 2 \cdots m \tag{20b}$$
$$y(t) = Cx(t) + f_{s_j}(t) \tag{20c}$$

where $c_j \in R$ is the j. row of the matrix C, $C^j \in R^{(m-1)xn}$ which is composed by deleting the j. row of the matrix C, $y_j \in R^{1xm}$ is the j. component of the y, $y^j \in R^{(m-1)}$ which is composed by deleting the j. row of the y.

Based on this description, m UIO-based residual generator can be constructed as [22]:

$$\dot{z}^j(t) = F^j z^j(t) + T^j Bu(t) + K^j y^j(t) \tag{21a}$$
$$r^j(t) = (I - C^j H^j) y^j(t) - C^j z^j(t) \quad j = 1, 2 \cdots m \tag{21b}$$

Each residual generator is driven by all inputs and all outputs except one output. When all actuators are fault-free and a fault occurs in the j. sensor, the residual will satisfy the following isolation logic:

$$\begin{aligned} &\left\| r^j(t) \right\| < T^j \\ &\left\| r^k(t) \right\| \ge T^k \quad for \quad k = 1, \ldots j-1, j+1, \ldots m \end{aligned} \tag{22}$$

where T's are isolation thresholds and $\left\| r^j \right\|$'s are the norm of the residuals. In this design the norm of the vector $\left\| r^j \right\|$ calculated as the length of its own.

To design robust actuator fault isolation schemes, all sensors are assumed to be fault-free and the system equations can be expressed as below [22]:

$$\dot{x}(t) = Ax(t) + Bu(t) + Bf_{a_i}(t) + Ed(t) \tag{23a}$$

$$y(t) = Cx(t) \quad for \quad i = 1, 2 \ldots m \tag{23b}$$

f_{a_i} represents the actuator fault vector.

Specified descriptions are:

$$d^i(t) = \begin{bmatrix} d(t) \\ u_i(t) + f_{a_i}(t) \end{bmatrix} \tag{24}$$

$$E^i = \begin{bmatrix} E & b_i \end{bmatrix} \quad for \quad i = 1, 2 \ldots m \tag{25}$$

$b_i \in R^{nx1}$ represents the i. row of the matrix B; $u_i(t)$ i. component of the vector $u(t)$.

Based on this description, unknown input observer residual generator can be constructed as [22]:

$$\dot{z}^i(t) = F^i z^i(t) + T^i B^i u^i(t) + K^i y(t) \tag{26a}$$

$$r^i(t) = (I - CH^i)y(t) - Cz^i(t), \quad i = 1, 2 \ldots m \tag{26b}$$

$B^i \in R^{nx(m-1)}$ is obtained from matrix B by deleting the i. row; $u^i(t) \in R^{m-1}$ is obtained from vector $u(t)$ by deleting i. component.

Each residual generator is used by all inputs and all but one faults. If the i. actuator fault occurs, the residual will be:

$$\begin{aligned} &\left\| r^i \right\| < \varepsilon^i \\ &\left\| r^k \right\| \ge \varepsilon^k \quad k = 1, \ldots i-1, i+1, \ldots m \end{aligned} \tag{27}$$

ε^i and ε^k represent the preset thresholds and $\left\| r^i \right\|$'s are the norm of the residuals. In this design the norm of the vector $\left\| r^i \right\|$ calculated as the length of its own.

2.2.1 Design procedure of UIO

Unknown input observer is stabilized $F = A_1 - K_1 C$ for design by choosing the matrix K_1, while the pair (C, A_1) is detectable. If (C, A_1) is not observable, an observable canonical decomposition should be applied. Unknown input observer design procedures are [22]:

1. rank (E) and rank (CE) are equal. If not equal, unknown input observer is not designed.
2. Find H, T and A_1:
   $H = E[(CE)^T CE]^{-1}(CE)^T$, $T = I - HC$
   $A_1 = TA$
3. If the pair (C, A_1) is observable, K_1 is computed.
4. If the pair (C, A_1) is not observable, observable canonical form is obtained. Firstly, an observable canonical form is performed:
   $PA_1P^{-1} = \begin{bmatrix} A_{11} & 0 \\ A_{12} & A_{22} \end{bmatrix}$ $CP^{-1} = [C^* \quad 0]$
   If one of the eigenvalues of A_{22} is not stable, unknown input observer is not designed. Observability matrix of (C, A_1) is selected as desirable eigenvalues and assigned to $A_{11} - K_p^1 C^*$. Then, $K_1 = P^{-1}K_p = P^{-1}[(K_p^1)^T \quad (K_p^2)^T]^T$ is computed. Here, K_p^2 can be any $(n - n_1)\ x\ m$ matrix
5. Find F and K: $F = A_1 - K_1 C$, $K = K_1 + K_2 = K_1 + FH$

Flow chart of design procedure is shown following:

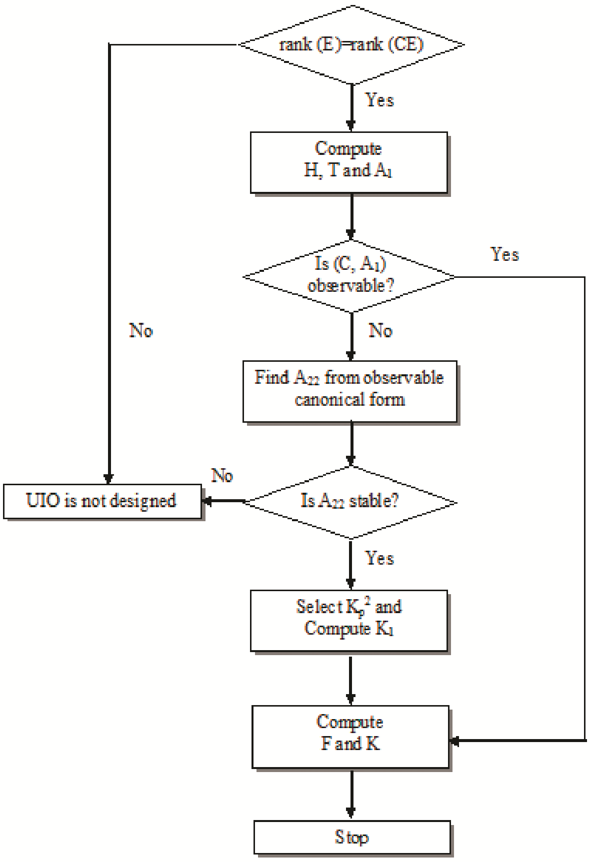

Figure 2 Flow chart of design procedure

3 Problem Solution

3.1 Accommodation

In passive fault tolerant systems, the system is maintained under control by intervention of robust control systems whereas in active fault tolerant systems first the fault is diagnosed then the control action is taken. The restructuring of the system and making possible the normal operation of the system after the detection and isolation of faults is referred to as reconfiguration. The faults are considered in the design stage of the system. The risk of losing completely all the system in case of the occurrence of an unimagined fault is the disadvantage of this approach.

In systems like airplanes in which movement is involved and high safety standards are needed, even actuator and sensor faults that take a few seconds are a threat to the safety of the system and we don't have the luxury of leaving these kind of systems to chance.

After solving detection and isolation problem, the system is accommodated as in Figure 3 for the actuator faults.

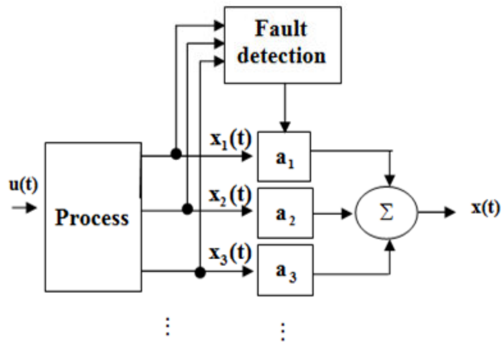

Figure 3 Suggested actuator accommodation

In Figure 3, the operation of the system composed of n actuators is shown. It is assumed that in case of a failure occurring in the actuators, the remaining components of the system will not be affected. It is also assumed that the sensors are redundant.

The new control law is realized by nulling the coefficients of the actuators displaying failure and increasing the value of the coefficients of the remaining actuators. For this purposes, the method may be used by changing the gains $a_1 \cdots a_n$ after detection and isolation for the actuator faults. All gains are 1/n when no fault is present in the system, while after detection and isolation the gain related with the faulty component is decreased to zero and all other gains are changed to 1/(n-1). The above situation can be described mathematically as for actuator faults:

no fault, $a_1 = a_2 = \cdots = a_n = \dfrac{1}{n}$

j. actuator fault, $a_1 = \cdots = a_{j-1} = a_{j+1} = \cdots a_n = \dfrac{1}{(n-1)};\ a_j = 0$

The new control law is also realized by switching redundant component for the sensors. These accommodation approaches can be used as decision logic for simulations.

3.2 Equations of Aircraft Motion

The equations of aircraft motion are obtained from Newton's second law by employing Taylor series expansion for multivariable functions to linear functions about the equilibrium points by considering the steady reference conditions. Using the steady space representation of the linear equations is useful for choosing the input vector which controls the surface's motions that affect the value of each state variable [21]. Generally, aircraft motions are classified as longitudinal and lateral motions. Lateral state variables and input vector may be defined as:

$$x = \begin{bmatrix} \beta \\ p \\ r \\ \phi \end{bmatrix}, \; u = \begin{bmatrix} \delta_a \\ \delta_r \end{bmatrix} \tag{28}$$

A and B matrices obtained from stability derivatives are described as:

$$A = \begin{bmatrix} Y_v & 0 & -1 & g/U_0 \\ L'_\beta & L'_p & L'_r & 0 \\ N'_\beta & N'_p & N'_r & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}, \; B = \begin{bmatrix} 0 & Y^*_{\delta_R} \\ L'_{\delta_A} & L'_{\delta_R} \\ N'_{\delta_A} & N'_{\delta_R} \\ 0 & 0 \end{bmatrix} \tag{29}$$

β is side-slip angle; p is roll rate; r is yaw rate; ϕ is roll angle; δ_a is aileron deflection; δ_r is rudder deflection; g is gravitational acceleration; U_0 is forward velocity, and others are stability derivatives.

A very large, four-engined, cargo jet aircraft's lateral model is as follows [21]:

$$A = \begin{bmatrix} -0.056 & 0 & -1 & 0.039 \\ -1.05 & -0.47 & 0.39 & 0 \\ 0.6 & -0.032 & -0.115 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \tag{30a}$$

$$B = \begin{bmatrix} 0 & 0.012 \\ 0.14 & 0.15 \\ 0.008 & -0.48 \\ 0 & 0 \end{bmatrix} \tag{30b}$$

Since the system is unstable it is stabilized by using the LQR method that computes the feedback gain matrix:

$$K = \begin{bmatrix} -6.1901 & 0.8445 & 6.3872 & 0.4051 \\ 2.7725 & -0.1573 & -3.4317 & -0.0128 \end{bmatrix} \tag{31}$$

Input vector and the observer dynamic matrix are chosen:

$$u = \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \; F = \begin{bmatrix} -10 & 0 & 0 & 0 \\ 0 & -10 & 0 & 0 \\ 0 & 0 & -10 & 0 \\ 0 & 0 & 0 & -10 \end{bmatrix} \tag{32}$$

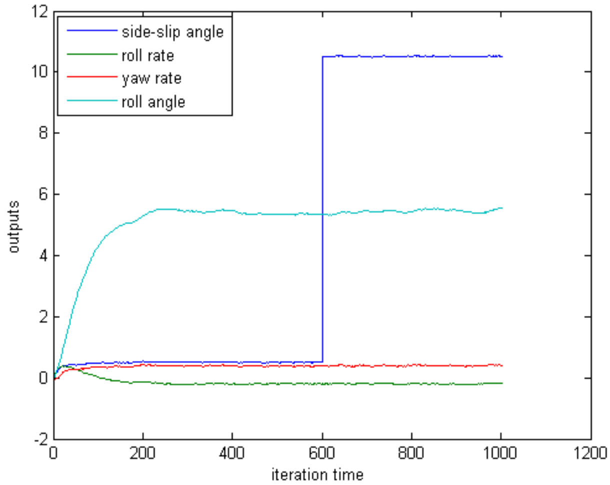

Figure 4 Outputs for sensor fault

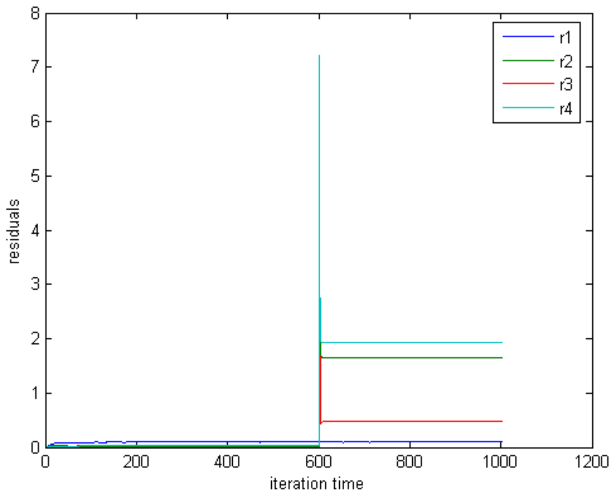

Figure 5 Residuals related with sensor fault

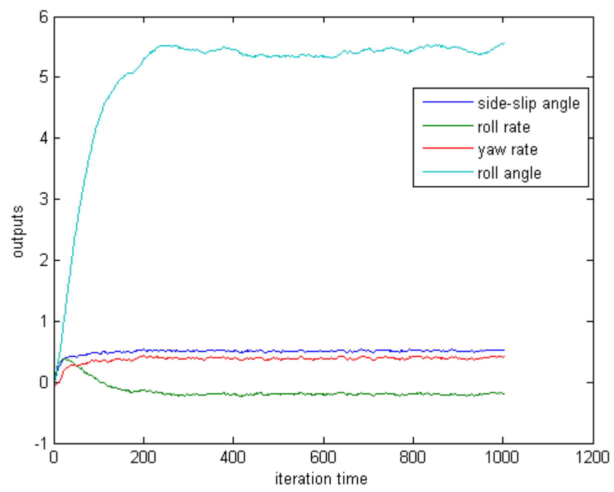

Figure 6 Sensor reconfiguration

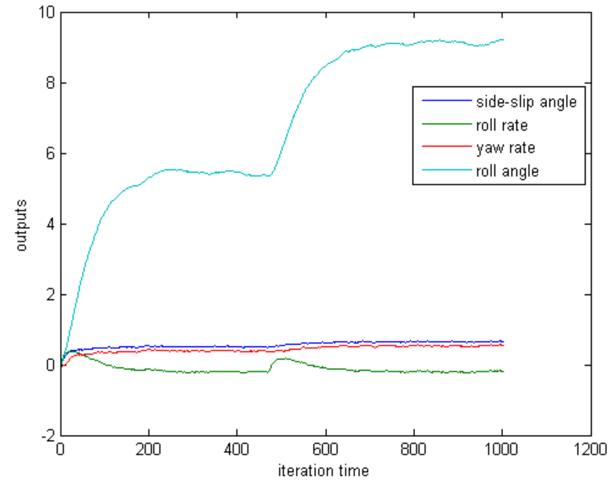

Figure 7 Outputs for actuator fault

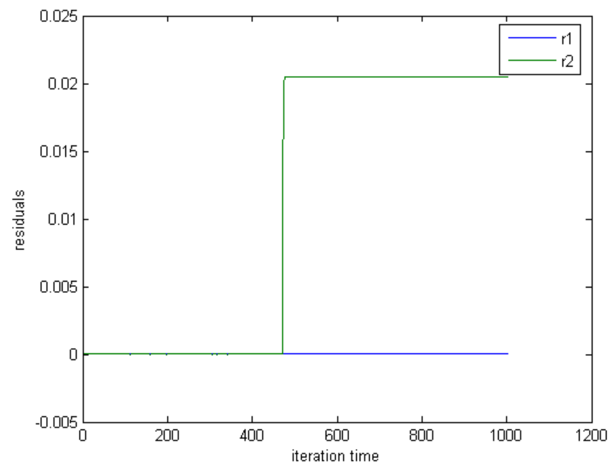

Figure 8 Residuals related with actuator fault

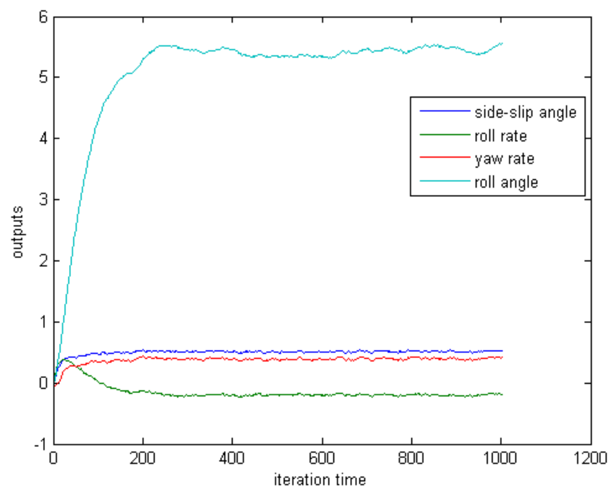

Figure 9 Actuator reconfiguration

A failure simulation prepared in "side-slip angle sensor" at iteration time = 600. The outputs of the flight condition are shown in Figure 4 when a failure occurs in sensor of side-slip angle. It is seen that side-slip angle has increased after 600 iteration. A sudden increase of any outputs does not have to imply a fault. Fault isolation is implemented by taking into account that each residual is sensitive to all of the other faults but one fault. By checking residuals, it is seen that after 600th iteration, the residuals r2, r3 and r4 exceed the threshold while r1 does not. By trial and error, it is determined that an acceptable value for this threshold is 0.07 for all the flight conditions. Accommodation is achieved by switching as shown in Figure 6.

It is seen in Figure 7 that all outputs have changed when an actuator fault takes place. Here, the fault is represented by the actuator corresponding to the aileron at 470th iteration. The outputs of the flight condition are shown in Figure 7 when a failure occurs in first actuator driving the aileron. By checking the residuals, it is seen that after 470th iteration, r2 exceeds the threshold whereas r1 does not. By trial and error, it is determined that an accepted value for the threshold is 0.005 for all the flight conditions and accommodation is achieved by gain scheduling as seen in Figure 9.

4 Conclusion

In this paper, we presented a robust sensor or actuator fault detection and isolation technique based on bank of Unknown Input Observers. In general, for linear observers, all inputs to the system are assumed to be available through measurements and used in the observer construction. However, as with disturbances, some of the inputs might not be available. In this case a type of observer should be designed which could predict the states of the system against the disturbances or unknown inputs. These advantages make UIO's more important than the linear observers. The unknown input decoupling conditions for a full order UIO are not very different from the other conventional observer schemes. However, a full order UIO provides more design freedom to achieve required performances. In real world, there exist unknown inputs such as system nonlinearities, noise and disturbances. For these purposes, it is simulated and tested on an aircraft model. When either a sensor or an actuator fault occurs, it can be detected, isolated and accommodated correctly. This paper shows that the fault tolerant system based on UIO is robust to unknown inputs mentioned above. Also this makes the system more flexible.

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