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LQG/LTR Controller with Fault Detection Method Based on Genetic Algorithms

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Abstract: - This paper presents a method for tuning Linear Quadratic Gaussian/Loop-Transfer Recovery (LQG/LTR) controller combined with a fault detection and isolation (FDI) filter design, which is applied and tested for F-16 aircraft by simulation. LQG/LTR controller is adjusted for design specifications, aided with a procedure where genetic algorithms are used for parameters tuning. The FDI filter is based on robust residual generator design via multi-objective optimization and genetic algorithms (MOO-GA), and it is made sensitive to roll and sideslip sensors. A systematic design procedure is proposed composed with two phases for LQG/LTR controller and for FDI respectively, by means of which design specifications are satisfied.

Key-Words: - Optimisation problem, genetic algorithms, flight control, fault detection, non-linear, LQG/LTR control, robust control.

1 Introduction

At present control systems are becoming highly complex and control algorithms more and more sophisticated. Consequently, the issue of available, reliability, operating safety are of major importance. For safety critical systems, the consequence of faults can be extremely serious in terms of human mortality and environmental impact. Therefore, there is a growing need for on-line supervision and fault diagnosis to increase the reliability of such safety critical systems [1] , [2] ,[6] ,[15] .

A traditional approach to fault diagnosis in the wider application context is based on *hardware redundancy methods* which use multiple sensors, actuators, computers and software to measure and control a particular variable. In *analytical redundancy schemes*, the resulting difference generated from the consistency checking of different variables is called as a *residual signal*. The residual should be sufficiently small (close to zero) when the system is normal operation, and should diverge from zero when a fault occurs in the system. This zero and non-zero property of the residual is used to determine whether or not faults have occurred. Analytical redundancy makes use of a mathematical model and the goal is the determination of faults of a system from the comparison of available system measurements with a priori information represented by the mathematical model, through generation of residual quantities and their analysis, [1] , [2] , [6] , [15] .

Significant advances to residual generation in model-based FDI approaches has been achieved [2] , [13] ,[15] such us: Kalman filter, diagnostic observers, parity relations and parameters estimation. Nevertheless, in both case the design parameters selection is difficult in order to achieve engineering specifications. Several optimization techniques, denominated as “intelligent” (genetic algorithms, neural networks, simulated annealing, tabu search), can be used for obtaining residual generator parameters directly, or in order to select design parameters [6] , [8] , [11] , [14] . In this work the second option has been implemented based on genetic algorithms (GA).

To ensure reliable operation of control systems, hard faults in system components are not tolerable and must be detected before they actually occur. Hence, the most important issue of reliable system operation is to detect and isolate incipient faults as early as possible. However, the detection of incipient faults presents a challenge to model-based FDI techniques due to the inseparable mixture between fault effects and modelling uncertainty. The fault can be detected by placing an appropriate threshold on the residual.

One common theoretical approach treats the modelling uncertainty as an additive disturbance term in the dynamics equation [1] , [2] , [6] , [15] . There are no requirements to use information about the distribution of the disturbance or uncertainty, although this information can be used if it is

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available. *Robust residual generation* can be considered as a multi-objective optimization problem, i.e. the maximization of fault effects and the minimization of uncertainty effects, [2] , [13] .

In this paper we introduce a optimal residual approach which is based on the combination of multi-objective optimization and genetic algorithm (MOOGA). In this approach the residual is generated via an observer. In order to make the residual insensitive to modelling uncertainty and sensitive to sensor and actuator faults, a number of performance indices are define to achieve good fault diagnosis performance. Some performance indices (PI) are defined in the frequency domain to take into account the fact that modelling uncertainty effects and faults occupy different frequency bands.

The numerical optimization technique is used to find the observer gain by means of eigenstructure assignment method. The information on frequency distribution ranges of faults, noise and modelling uncertainty can be incorporated into a robust residual design. In this paper we use the method of inequalities to solve this multi-objective optimization problem, the genetic algorithm (GA) is used to search an optimal solution to satisfy inequality constraints.

The rest of the paper is organized in sections as follows: in section two the proposed procedure based on MOO-GA for robust residual generator design is described, in section three FDI system is applied to a fault tolerance flight control system and simulation results are analyzed in section four; finally, conclusions are resumed.

2 Robust Residual Generator

The residual generator shown in figure 1 is based on a full-order observer. The idea is to estimate the system output from the measurements using an observer. The weighted output estimation error is then used as a residual.

In order to achieve robust FDI a multi-objective optimization problem will be solved by means of four performance indices. The observer design problem can be formulated in its dual form as a controller design problem, so that techniques for controller design can be applied. In this paper, the *eigenstructure assignment method* is chosen to get a satisfactory gain matrix K_{or}, which, at less, must guarantee the stability of the observer,[2] , [3] , [9] , [10] , [13] .

A solution which minimizes multiple performance indices (MPI) can not exist in practice, and therefore some compromises and trade-offs must be considered for solving the design problem. The trade-offs are based on relative importance of objectives. The MOO can be solved using numerical search algorithms. In this work, we have used the method of inequalities.

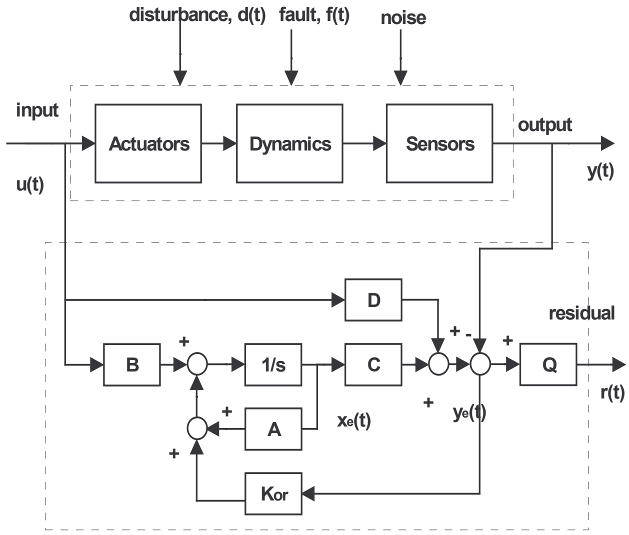

Fig. 1. Robust residual generator block diagram.

The main philosophy behind the method of inequalities is to replace the minimization of the MPI by an inequality constraint on the MPI. The optimisation problem is posed as the satisfaction of a set of inequalities, rather than the minimization of some objective functions with inequalities acting as constraints.

For the robust residual generator problem, the MOO problem is being reformulated into that of searching for a design parameter set $\{Z,W,Q\}$ to satisfy the following inequalities:

$$J_i(Z,W,Q) \le \varepsilon_i, \quad i = 1,2,3,4 \tag{1}$$

where the real number ε_i represents the numerical bound on the PI required by the designer. If $J_i^*(Z_i^*, W_i^*, Q_i^*)$ is the minimal value of $J_i(Z,W,Q)$, as a general rule, the performance boundaries ε_i should be set as:

$$J_i^*(Z_i^*, W_i^*, Q_i^*) < \varepsilon_i \le \max_{j \ne i, j\in[1,4]} \{J_i^*(Z_j^*, W_j^*, Q_j^*)\} \tag{2}$$

The problem of MOO is to find a parameter set to make all performance indices lie in an acceptable region. By adjusting the bounds, different emphasis on each of the objectives can be placed. Zakian suggests an algorithm for satisfying the inequalities which it is called the *moving-boundaries algorithm*. The Genetic optimization version of this algorithm have been implemented in this work to solve the

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multi-objective optimization problem by means of the method of inequalities, [2] , [7] , [10] , [13] .

2.1 Design Procedure

In order to design a robust FDI system we have implemented a robust residual generator design procedure, which uses genetic algorithms (GA) to solve multiple objective optimization problems.

The following steps are considered in our design methodology:

Step 1: Four frequency weighting penalty functions are selected to separate the effects of noise and disturbances of faults, where the plant dynamics will be take into account.

Step 2: In order to search the interval of values for ε_i that satisfies (2), MOO-GA algorithm is executed and performance indices are minimized individually.

Step 3: The bounds are selected from the intervals computed in step 2; with this, relative weighting performance indices are selected. Adjusting the bounds ε_i one can place a different emphasis on each of the objectives.

Step 4: Sensor and Actuator fault residual generator is designed via MOO-GA. The observer gain matrix K_{or} is computed by means of design parameters to achieve robust FDI, a multi-objective optimization problem will be solved.

Step 5: The detection thresholds are selected taking into account incipient faults detection and false alarms rejection. Adaptive threshold and/or several levels of safety can be implemented.

Step 6: Simulation results of the plant are analyzed in order to evaluate the FDI system.

Step 7: If simulations results are not satisfactory, Go to *step 3*; else *End procedure*.

3 Fault Detection and Isolation Application

In this section, we shall illustrate the MOO-GA technique for a FDI system design applied a lateral aircraft control augmented system (CAS). The sensor fault detection filter is sensitive to roll and sideslip sensors. The actuator fault detection filter is sensitive to ailerons and rudder actuators. The FDI filter is implemented in linear and non-linear F-16 aircraft and is tested by means of LQG/LTR lateral track controller.

The tracking control system and aircraft lateral dynamic is meant to provide coordinated turns by causing the bank angle $\phi(t)$ to follow a desired command while maintaining the sideslip angle $\beta(t)$ at zero. It is a two-channel or MIMO system. Computations and simulations have been implemented using MATLAB environment, Simulink, the Control System Toolbox and the GA toolbox, [4] , [5] , [10] , [12] , [16] .

3.1 FDI Objectives

One of the biggest challenges in design of flight control system (FCS) is a requirement for the flight of the aircraft to recover safely from structural damage and/or system faults. Reliable fault diagnostic information is extremely important to the pilot. Prompt presentation of fault information to the pilot could enable him to take accommodating action to the malfunction, using system redundancy. Sensors are the most important components for flight control and aircraft safety due to its roles in flight control and navigation. Any sensor fault must be detected as early as possible to prevent serious accident.

To diagnose incipient faults, a FDI system will be made robust against modelling uncertainty and noise. The technique presented in this paper is used to design robust residuals to diagnose incipient sensor faults in a FCS, [4] ,[16] ,[17] .

3.2 Design Procedure

Sensor residual generator. An observer is designed to generate sensor residual signal for FDI. The effects of noise and faults can be separated by selecting different frequency weighting penalty functions and including into performance indices expressions (*step 1*):

$$
\begin{aligned}
W_1(s) &= \frac{200}{(s+5)(s+40)}, \quad & W_2(s) &= 1 \\
W_3(s) &= \frac{1}{W_1(s)}, & W_4(s) &= 1
\end{aligned} \tag{3}
$$

which places emphasis on the residuals at low frequencies and on noise at high frequencies.

To apply the method of inequalities, we begin searching for the ε_i values intervals that satisfy (2), MOO-GA algorithm is executed and performance indices are minimized individually. Table 1 lists the MPI for different observer gains. In this table, K_i^* represents the observer gain matrix which minimizes J_i (i=1,2,3,4). It can be seen that a design which minimizes a particular performance function makes all other performance functions unacceptably large (*step 2*).

In order to use the method of inequalities to solve this problem, a set of MPI bounds ε_i is chosen as shown in the table 1 (bounds row) (*step 3*). Sensor fault residual generator is designed via MOO-GA (*step 4*).

TABLE 1. Performance indices for different designs

	J_1	J_2	J_3	J_4
K_1^*	**0.47**	29580.25	2004.05	101169.61
K_2^*	15.30	**1274.74**	2033.55	11441.93
K_3^*	4.45	10312.98	**2002.11**	54472.70
K_4^*	36.44	946.41	2008.58	**90.23**
Bounds	500.00	3000.00	3000.00	200.00

Actuator residual generator. The same procedure is applied to the observer design to generate actuator residual signal for the FDI system. In this case, Table 2 list the MPI for different observer gains.

TABLE 2. Performance indices for different designs

	J_1	J_2	J_3	J_4
K_1^*	**585.04**	3705.49	2150.07	13779.28
K_2^*	76673.06	**7.21**	750485.20	34917.65
K_3^*	611.12	14855.85	**2002.13**	605425.77
K_4^*	609.44	1119.94	2009.05	**87.60**
Bounds	1000.00	500.00	3000.00	200.00

3.3 Fault Description

Sensor fault. The inertial navigation system (INS) detects aircraft motion and provides acceleration, velocity, present position, pitch, roll and true heading to related systems. Typical inertial navigation unit contains a gyro stabilized platform which contains three accelerometers and two gyros which are isolated from external angular motion by a set of four gimbals. Each accelerometer is mounted so that the unit is sensitive to motion on a specific axis. The accelerometers provide accelerations for system computations. The gimbals position provide 360º freedom of rotation. The gyros provide the stabilization of the platform to maintain accurate outputs. The INS must be alignment before take-off, a bad alignment provides excessive tolerance for errors and must be considered a fault in roll and sideslip angle sensors since sideslip is computed by

$$\dot{\beta} = \frac{\dot{v}V_T - v\dot{V}_T}{V_T^2 \cos\beta} \tag{4}$$

where v is the lateral velocity and V_T is the true airspeed, [4] , [9] , [16] .

Actuator fault. Typical lateral and rudder control system consists of the control stick, pedals, high speed stop unit, spring feel *unit*, trim actuator, cables, control rods, hydraulic actuators and control surfaces. One or more of these elements can be degraded due to fatigue and must be considered a fault in actuators command position, [4] , [16] .

4 Simulation Results

During design process we have carried out simulation tests using linear and non-linear model of the plant.

4.1 Linear model of the plant

The simulation is used to assess the performance of the observer-based residual generator in the detection of incipient sensor and actuator faults. The control command (set point) for roll angle is a unit step and for sideslip angle is zero. To take into account noise in sensors and actuators, control channels are perturbed by means of band-limited white noise. In order to detect incipient faults in sensors and actuators, incipient faults are modeled by means of 0.01 deg/s ramp signal.

The simulated fault is added to the roll angle sensor. To illustrate the small nature of the incipient fault, Fig. 2 shows the plot of both sensor (faulty) and observer measurements of the roll angle $\phi(t)$. The fault takes place at the 2 sec., the residual signal activates the alarm when the signal reaches the threshold (t = 5 sec).

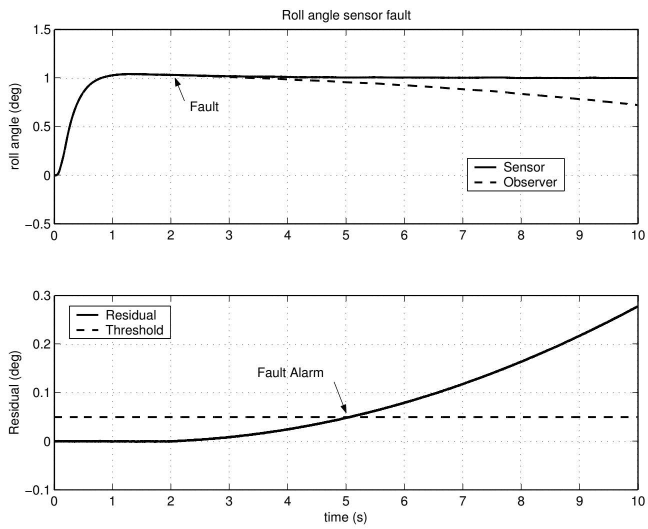

Fig. 2. Roll angle sensor fault.

A new simulated fault is added to the sideslip angle sensor. The simulation result of the FDI filter can be seen in Fig. 3, the residual shows a noisier signal due to the fact that $\beta(t)$ is computed by means of discrete version of (4). Incipient fault alarm take places at 5.3 sec, when the error is smaller than 0.01 degrees.

Another type of fault take places when an actuator (ailerons or rudder) has a loss in effectiveness. Fig. 4 and 5 show the plots of both aileron and rudder actuator faults. Respective faults take place at 2 sec., the residual signals activate alarms when the signals reach the threshold at 3.0 and 3.4 sec, respectively.

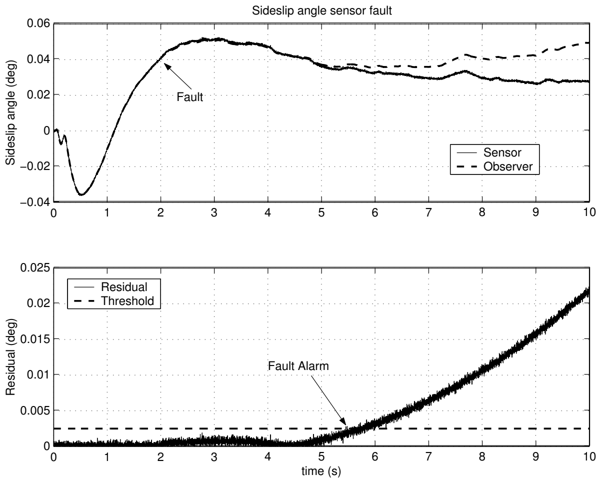

Fig. 3. Sideslip angle sensor fault.

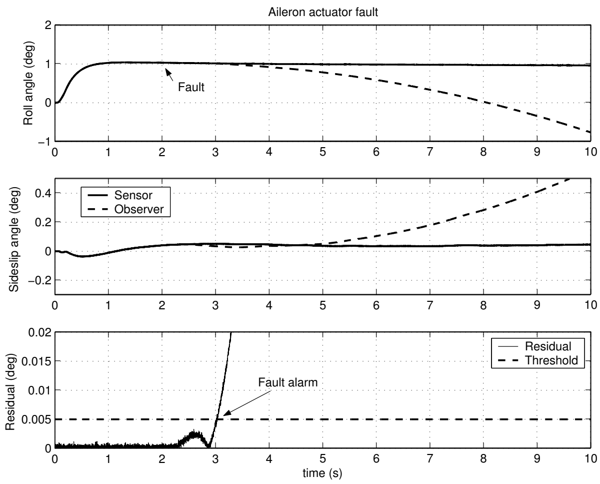

Fig. 4. Aileron actuator fault.

From the analysis with the linear model of the plant we have obtained that FDI filter shows good properties, due to the fact that fault alarm signals are activated when the fault is incipient. The thresholds detection are set with a sufficient margin to avoid false alarms.

4.2 Non-linear simulation

The next step in the analysis and design procedure is to test the FDI filter with the non-linear model of the plant. As in linear case, the sensors and actuators control channels are perturbed by means of band-limited white noise and the faults are modelled by means of 0.01 deg/s ramp signal.

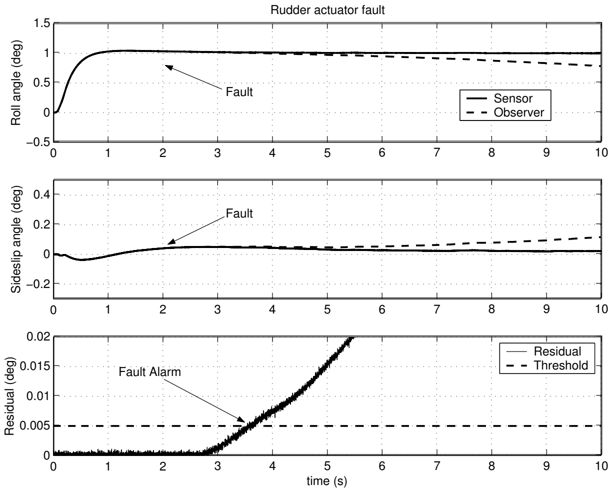

Fig. 5. Rudder actuator fault.

Fig. 6 and 7 show sideslip sensor and aileron actuator faults. As it can be seen, very similar behaviours are obtained from comparison with Fig. 4 and 5 (linear model simulations), respectively.

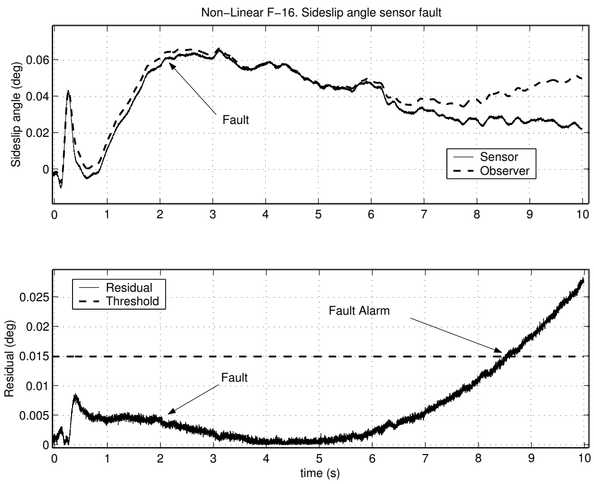

Fig. 6. Non-linear F-16 sideslip sensor fault.

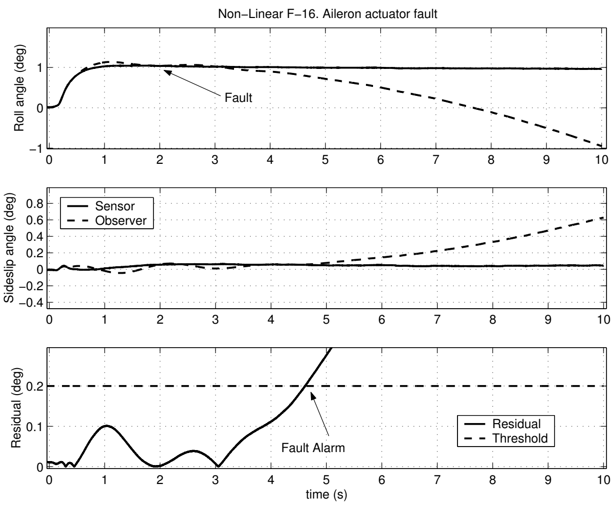

Fig. 7. Non-linear F-16 Aileron sensor fault.

In order to test the FDI system robustness and behaviour for flight conditions different to nominal case, closed loop simulations are made with a fixed observer. This can be seen in Fig. 8, where the fault takes place at 2 sec and satisfactory behaviour is obtained. In order to achieve incipient fault detection and false alarm rejection, the threshold must be increasing for non-nominal operation of FDI system. For greater variations in flight conditions a new observer must be designed for good performance.

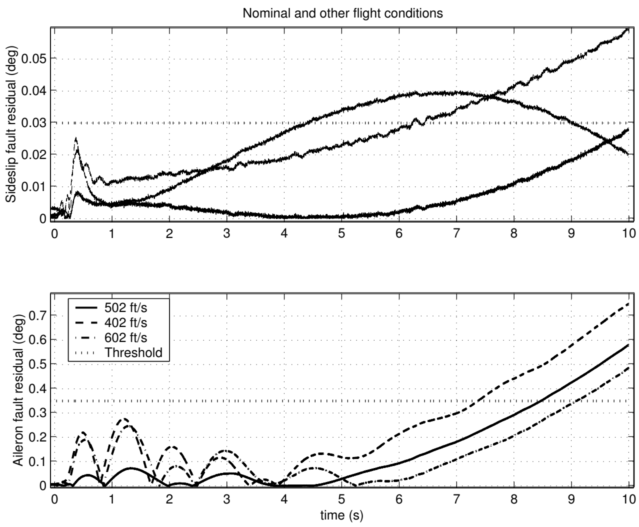

Fig. 8. Another flight conditions comparison.

5 Conclusion

In this paper a systematic procedure for FDI system design has been presented and applied. The FDI system is designed for robustness and incipient faults detection requirements that are obtained using multi-objective optimization and genetic algorithm.

Incipient fault detection, suitable time responses as well as satisfactory robustness properties are obtained, where genetic algorithms are employed to satisfy design specifications for a fault tolerance flight control system.

Our work combines a robust FDI technique and a robust numerical optimization method (GA).

In future works, an expert system based on design specifications and plant knowledge will be incorporated for selecting the design parameters and for adapting controller and FDI system to different flight conditions.

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