Proceedings of the 8th IEEE Mediterranean Conference
on Control and Automation (MED 2000)
Rio, Patras, GREECE 17-19 July 2000

WEAK MODEL BASED FAULT DETECTION AND IDENTIFICATION IN FLIGHT CONTROL SYSTEMS*

ODED M. GOLAN†, MOSHE IDAN†, RON MEIR‡

†Technion, Israel Institute of Technology, Department of Aerospace Engineering, Haifa 32000, Israel, asgolan@tx.technion.ac.il, aeridan@aeron.technion.ac.il
‡Technion, Israel Institute of Technology, Department of Electrical Engineering, Haifa 32000, Israel, rmeir@tx.technion.ac.il

Abstract. This paper deals with fault detection and identification (FDI) of sensor failures in an aircraft flight control system. The proposed FDI algorithm only weakly depends on a specific model of an aircraft. The advantage of such an FDI algorithm is the possible reduction in the flight control system complexity and cost due to the reduced number of redundant hardware components required to ensure safe flight operation in cases of failures. The non-model based approach is in particular attractive because it could provide an FDI algorithm suitable for implementation on a variety of aircraft with only minimal adjustments required when using it on a specific aircraft, thus reducing the development cost. The current paper focuses on non-distinctive sensor failures that are identified using dissimilar sensor information. The proposed FDI algorithm was favorably tested using a realistic simulation model of a small civil aircraft.

Key Words. Fault detection and identification, fault tolerant flight control, Neural Networks, Wavelet Transform.

1. INTRODUCTION

The progress in computer technology has lead in recent years to its intensive utilization in primary flight control functions of military and, more recently, large civil transport and cargo aircraft. The great flexibility of computer based control systems has resulted in an overall increase in the complexity of the "fly-by-wire" technology, including the incorporation of new performance enhancing functions (envelope protection, maneuver limiters, etc.) and the use of novel control design techniques in the flight control systems synthesis. The increased complexity of the computer based control systems has lead also to the inevitable requirement for reliability and flight safety, especially in open-loop unstable fighters and large civil aircraft.

* This research was supported by the European Community through the Brite Euram III project BE97-4098.

To comply with the strict safety requirements imposed by the civil aircraft certification authorities, fault tolerant flight control system design methodologies had to be derived. To conform with these requirements, most of the computer based flight control systems rely solely on hardware redundancy, where a number of similar sensors are installed on an aircraft to ensure correct data flow into the flight controller. In these solutions, faults are identified and accommodated by relatively simple heuristic majority voting and monitoring algorithms. To obtain high reliability, often four and more similar sensors are used for critical flight data channels. If such a redundancy can be implemented (depends on cost, development time, physical installation limitation, etc.), the standard voting and monitoring techniques provide a sufficient solution. The main drawback of these solutions is the increased complexity and cost of the system, making them suitable mainly for large civil transport aircraft.

To make these digital flight control systems affordable for small commercial aircraft applications, new design technologies are required to reduce the complexity and cost of the control system. This is the goal of an ongoing project entitled: "Affordable Digital Fly by Wire Flight Control System for Small Commercial Aircraft (ADFCS)", sponsored by the Science Commission of the European Community. The project is carried out by a consortium of seven European aerospace industry and research organizations. Among other cost driving factors, the project aims at reducing the hardware redundancy without compromises with flight safety requirements. This is obtained by incorporating "analytical redundancy" techniques in the flight control system design, where information from dissimilar sensors is used to identify faults. A reasonable cost reduction of the digital flight control system will enable its installation on small commercial aircraft.

Fault detection and identification (FDI) using analytical redundancy techniques is thoroughly covered in a many research and survey papers, accounting for over three decades of intensive research effort [1, 2, 3]. Most of these techniques rely strongly on an analytical model of the physical system, making them sensitive to modeling errors. Full flight envelope operation of the aircraft imposes a continuous change in the aircraft model and thus requires continuous variation in the FDI algorithm. To overcome these drawbacks of analytical redundancy techniques and in order to make the FDI algorithm applicable to many different aircraft, with only minimal adjustments required when adapting it to a specific aircraft, a non-model based solution would be more desirable. This would greatly reduce the development costs, and thus favorably affect the final cost of the end product - the single flight control system.

In the ADFCS project, the Technion team is working on designing FDI algorithms that only weakly depend on the aircraft model. For that purpose, the possible sensor faults were categorized into two classes: distinct and non-distinct faults. In effect, the non-model based methods replace the need for the system (aircraft) model by one that describes the fault characteristics. The distinct faults include sensor disconnects, bias jumps, hard-overs (output stuck at the sensor limits), and sometimes signal freezes. In a previous paper [4] it was shown that these faults can be reliably identified using a simple wavelet transform, a dynamic threshold logic and a simple neural-network based classifier. The main advantage of that algorithm is that a fault can be detected by processing the data coming from each sensor independently.

A much more difficult problem relates to faults and changes occurring on a slower time-scale, that may be similar to a normal response of the aircraft. Such changes do not possess distinctive features of a fault and therefore the previous approach may fail. The purpose of the current study is to propose weak model based FDI algorithms for non distinctive faults such as a slow drift. In particular, these algorithms are aimed to tackle the 1-vs-1 case, where only two similar sensors of a particular data channel are available. In case of discrepancies between their readings, it is desired to identify the faulty signal. In standard voter monitor solutions, differences of readings in the 1-vs-1 case result in a total loss of the data channel and requires an immediate control system reconfiguration into a degraded control mode. The proposed approach to identify the fault in this case will provide an additional level of redundancy, allowing either a prolonged nominal operation or a reduction in the hardware redundancy.

2. THE CONCEPT

Aircraft dynamics, and in particular that of a closed loop controlled commercial airplane, can be described quite accurately by a linear model, in which well known modes of behavior appear in some measured quantities more than in others. Typically, longitudinal and lateral dynamics are well separated. Within each of these controlled dynamical modes, some measured variables are more tightly related than others. For instance, normal acceleration is strongly related to the angle of attack, which in fact causes it through aerodynamic phenomena. Pitch rate is obviously related to pitch attitude through a simple kinematic relation, roll attitude to yaw rate (assuming coordinated turn), and so on. Therefore, we may expect to find "signatures" of maneuvers or mode excitations in the related variables.

A fault in one sensor will introduce a new signature in the measured signal that should not appear in any other measurement, unless the corrupt signal is used to control the aircraft. In this case a few sensors may show responses somewhat reminiscent to the fault. Hence, if the measurement is not fed back through the closed loop control system, the signature of the fault will not appear in the related measurements or in the output of a different sensor measuring the same physical quantity or other related variables. In equilibrium conditions such as during straight and level flight, a drift (or any other non-distinctive) fault will clearly introduce a dynamic signature that can be easily distinguished from the static behaviour of the other uncorrupted signals. In the case where the faulty signal is fed back into the system, the fault becomes an external (undesired) input and all related sensors will manifest its signature to some extent. If no intentional maneuver is imposed, the faulty sensor can be identified based on careful examination of the time evolution of the sensors' outputs. Therefore, in the FDI approach suggested in this paper the fault identification process is performed only during nearly steady state operation, which covers most of the flight time of a commercial aircraft.

Non linear filtering can be used in order to identify the dynamic features of the faulty signal. In Ref. 4 distinctive fault identification used similar analysis which was inspired by wavelet transform methods. The signal was processed by a convolution operation with a typical base function. The Haar wavelet, shown in Fig. 1, was used as the base function. It contains a discontinuity that served to emphasize a similar feature in the monitored signal. The convolution result, known as the first detail in the wavelet transform, contains a magnified discontinuity at the time instance where an abrupt change in the signal is present. The effect of the Haar wavelet transformation is similar to high pass filtering. It can be regarded as a discrete differentiation operation which is averaged by the convolution over a limited interval.

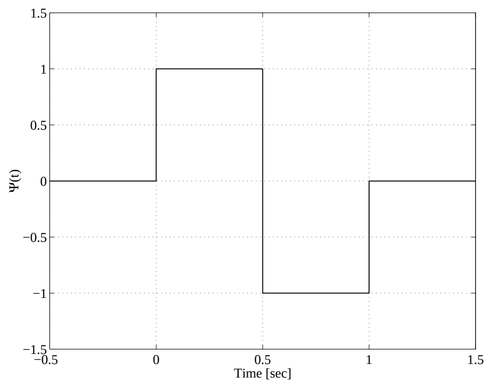

Figure 1: The Haar wavelet function.

An approach similar to the one discussed above is applied to the case of slow drift faults. The Haar wavelet transformation serves to emphasize the slope of signal. In the sequel, FDI of non-distinctive faults for open and closed loop signals are discussed separately.

2.1. Slow Drift in an Open Loop Signal

In the open loop situation, where a signal (sensor) of interest is not used in a feedback control system, a 1-vs-1 case of a non-distinctive fault can be isolated by comparing the two similar signals to a related (reference) signal. In addition, in order to identify a nearly steady state operation, a relevant pilot command is also used for FDI. For example, while considering aircraft sensors that measure one of the longitudinal variables, the pilot elevator commands would be used.

The proposed FDI procedure is activated if the difference between the two monitored signals exceeds a certain threshold. The threshold level depends on the particular application. Transformed signals, obtained by convolution with the Haar base wavelet described above, reveal the existence of a slope. In a steady state situation the reference signal should contain no dynamics, and therefore its first detail should remain small. In the presence of a slow drift, the first detail of the faulty signal would stand out. This information can now be processed with adequate logics to identify the fault and to examine the persistence of the slope to minimize false fault alarms. This processing can be efficiently accomplished by a perceptron neural network, which is widely used for classification applications [5].

A perceptron is a simple non linear neuron that is built around a hard limiter and is fed by a linear combination of the inputs and a bias. A further modification of the neuron is to feed also a few delayed inputs through the so called "tapped delay line". The result is in fact a combination of the perceptron and an adaptive feedforward neural network. One possible implementation of such a network consists of the following three layers:

- A first hidden layer consists of 4 perceptrons with tapped delay lines on the input. Each perceptron is fed by a separate signal (the wavelet transform of the two monitored signals, the reference signal and the related pilot command). The delayed data is used to average the information over a finite interval and "filter out" the high frequency components of the signals, that may result from measurement noise. The bias signals are external inputs that define a threshold for the test. The selection of these thresholds can be done either manually by the designer who is intimately acquainted with the expected behaviour of the aircraft, or by network training procedures which use representative data.

- A second hidden layer composed of two perceptrons, each fed by the four outputs of the first layer and combining the inputs in order to identify a fault in one of the observed signals. The input weights and bias are predetermined such that a flag will be raised (i.e., the output of the neuron will switch to 1) when the expected combination of inputs or events occurs.

- An output layer of one modified perceptron with a delayed input. The purpose of this layer is to check the persistent presence of a faulty feature. Increasing the number of delays in the tapped delay line of this perceptron will reduce the false alarm rate at the cost of increased time required to identify a fault.

2.2. Slow Drift in a Closed Loop Signal

The FDI task is more complex when the drift fault appears in one of the sensors used in a closed loop control system. The fault affects the control system similarly to an external input or a pilot command. As a consequence, the control system will command an aircraft motion to comply with this input. The response of the aircraft will be sensed by all the faulty and non-faulty sensors that measure quantities related to the same physical phenomenon. In addition, the closed loop characteristics of the controlled aircraft tend to reduce the overall effect of the sensor fault on the dynamic response of the system. This excludes a direct adoption of the previous procedure to identify this drift.

However, a close examination of a typical feedback architecture reveals that there is a significant difference between the direct effect of the fault on the faulty sensor and the readings of other sensors that measure the fault through the system dynamics. Figure 2 shows a simple feedback control system with two identical sensors s_1 and s_2 that measure the same output y, one of them contaminated by an additive fault d. The average of the two readings is fed back into the controller. It is clear that the response of an appropriately designed feedback system is to reduce the tracking error, thus the response would tend to balance the undesired input. If the fault appeared during steady flight conditions with no pilot maneuvering commands, the slope of the output will be in the opposite sense to the input drift (the fault). If, in addition, a measurement of a related signal is available, provided that the quantitative relationship between the various signals is known, it is possible to use this additional signal as a reference and develop a fault detection algorithm similar to the one proposed for the open loop case. The success of this approach strongly depends on the dynamic characteristics of the monitored and reference signal chosen.

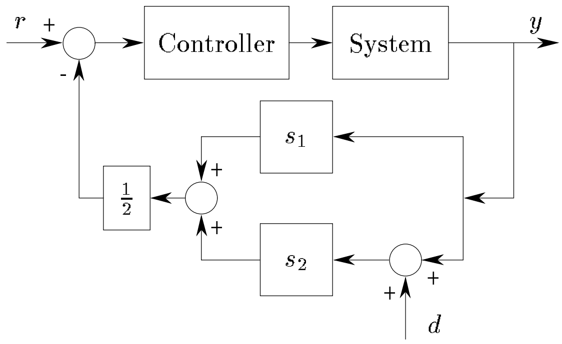

Figure 2: A simple feedback control system with two identical sensors (1-vs-1 case).

Again, the algorithm is initiated when the two monitored sensors are in disagreement, as indicated by a difference in their readings that exceeds a prescribed threshold. Also, the test will not be enabled as long as there is an external command input by the pilot. The same wavelet analysis can be implemented to determine the slope of the signals, which are then fed to a similar classifier neural network whose role is to identify the signal that disagrees with the reference.

3. EXAMPLES

The generic Small Commercial Airplane model used in the ADFCS project was utilized in numerical simulation evaluations. This relatively realistic aircraft model, implemented in the Matlab/Simulink environment, includes six degrees of freedom dynamics model of the aircraft, a complete digital flight control system capable of operating in the entire flight envelope, redundant sensors and actuators models, as well as classical voter-monitor FDI algorithms. The atmospheric model includes slow winds and turbulence, while the sensor modules contain measurement noise and various fault types models.

An on-line FDI algorithm is implemented in order to monitor slow drift faults in the angle of attack and in the pitch attitude sensors. It is assumed that there are 2 angle of attack sensors and 2 attitude sensors. Angle of attack measurement is used for gain scheduling and pitch command limiters and therefore, under normal conditions, can be considered as an open loop measurement. The attitude sensor is used in the pitch control channel to control the pitch position. Thus, these measurements represent the two types of measurements described above. Since there is a direct relation between the angle of attack and the normal acceleration, the measured normal acceleration can be used as a reference signal for angle of attack monitoring. Similarly, the pitch rate is related to the pitch attitude and thus the pitch rate measurement is used as a reference signal for the pitch angle. In addition, the pilot's pitch command is assumed to be available through a measurement of the column motion.

For the open loop case, the algorithm is monitoring each of the angle of attack sensors. The voted (averaged) normal acceleration measurement is used as a reference. The first detail of each of these quantities is generated and supplied to the neural network classifier. In the closed loop case, the algorithm is monitoring each one of the pitch attitude sensors. The voted (averaged) pitch rate measurement is used as a reference signal.

Figure 3 shows the two measurements of the angle of attack. The faulty signal is drifting away at a rate of 0.5 deg/sec, starting from time $t = 1$ seconds. The reference signal, the averaged normal acceleration, is shown in Fig. 4. The fault identification is delayed due to the pitch maneuver. The pitch command returns to zero at $t = 11$ seconds, however the transient response lasts few more seconds and further delays the identification. The first details of the measured angles of attack are depicted in Fig. 5. The drift signature in the faulty measurement appears as a bias. The transient response of the "healthy" signal converges and stays below the selected threshold at $t = 13$ seconds. The detail of the acceleration, given in Fig. 6, is similarly converging to small amplitudes with zero average. A further delay of 5 seconds is imposed by the persistency test which is conducted by the classifying network. The fault flag is raised by the network at $t = 18$ seconds.

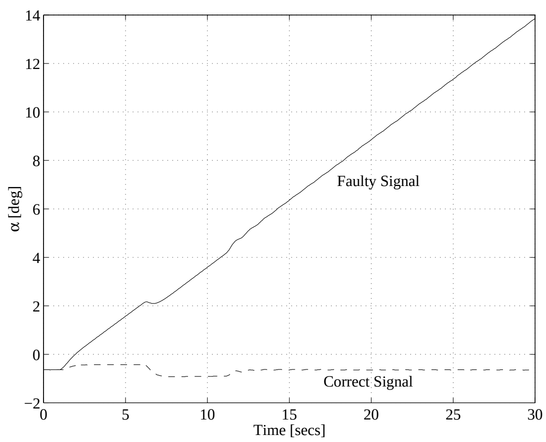

Figure 3: Angle of attack measurements. A drift of 0.5 deg/sec is introduced in measurement #1 at $t = 1$ seconds.

The closed loop example is shown in Figs. 7 and 8. One of the pitch attitude sensors develops a drift

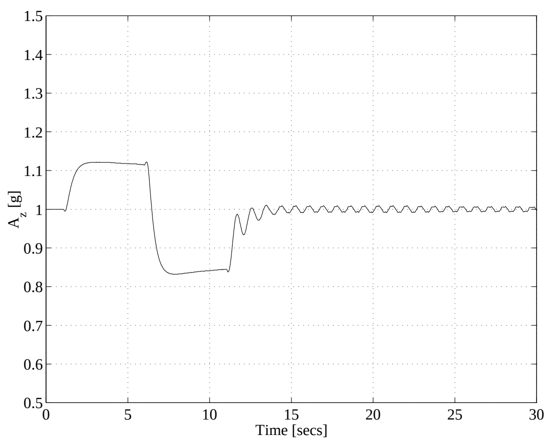

Figure 4: The voted normal acceleration.

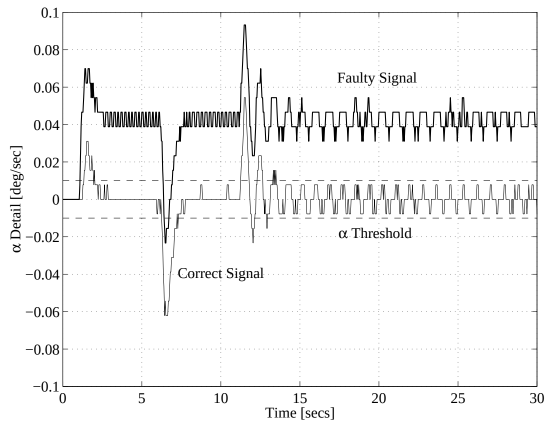

Figure 5: The first detail of the angle of attack measurements.

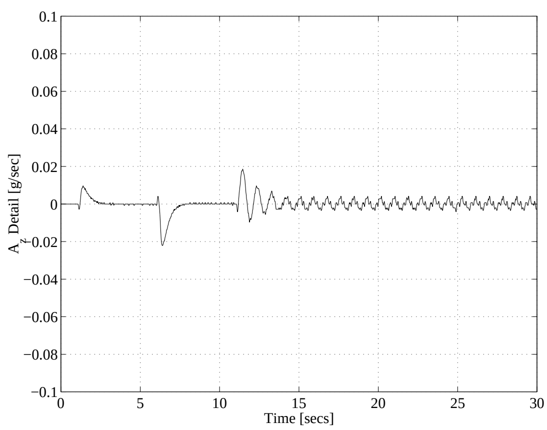

Figure 6: The first detail of the normal acceleration.

fault starting at $t = 2$ seconds. As a result, the voted attitude, which is the average of the readings of the two available sensors, is drifting away at a rate that is in between the faulty and correct signals rates. The feedback control system is responding to the drift introduced by the voted signal, and the aircraft is developing an undesired pitch manuever in the opposite direction to the drift. This can be seen in the output of the correct attitude sensor and in the pitch rate measurement. The fault is identified at $t = 6.5$ seconds, and as a result, the voted signal switches to the correct signal, ignoring the faulty measurement. The identification time delay includes 5 seconds allocated to the persistency test. The abrupt switch of the attitude signal is inducing a large transient response, as can be seen in the pitch rate sensor readings. In real aircraft design, this transient can be reduced by introducing proper filtering in the switching process. After the transient, the aircraft returns to a steady state flight, using one attitude sensor.

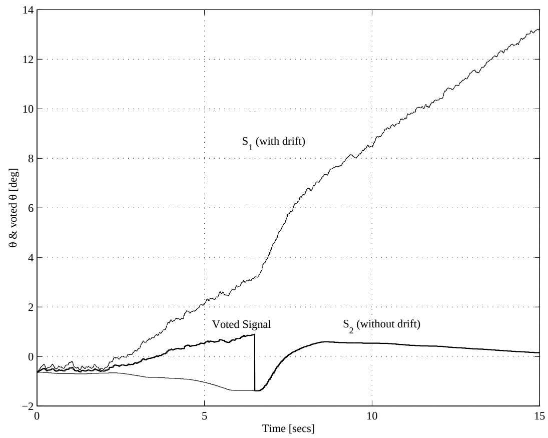

Figure 7: Closed loop pitch attitude measurement. Sensor #1 develops a drift fault at a rate of 1 deg/sec starting from $t = 2$ seconds. The fault is identified at $t = 6.5$ seconds.

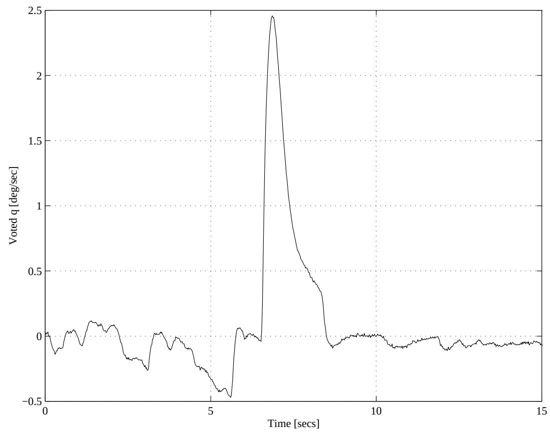

Figure 8: Pitch rate measurement.

4. CONCLUSIONS

The use of analytical methods to solve the FDI problem can reduce hardware redundancy and lower the cost of flight control systems. Weak dependence on the aircraft model is desirable. This paper addresses the problem of FDI for non-distinctive faults, i.e., faults whose features are similar to those of the correct signals. Identification of such faults requires comparison to other signals and some knowledge of the system model and dynamic characteristics. The methods discussed in this paper exploit the functional dependence between various measured signals in order to identify the fault using the wavelet transform and neural network techniques. The favorable performance of the proposed approach is demonstrated numerically for a model of a small commercial aircraft.

REFERENCES

[1] Frank, P. M. Fault diagnosis in dynamic systems using analytical and knowledge based redundancy - a survey and some new results. *Automatica*, 26(3):459–474, 1990.

[2] Isermann, R. and Ballé, P. Trends in the application of model-based fault detection and dignosis of technical processes. *Control Engineering Practice*, 5(5):709–719, 1997.

[3] Chen, J. and Patton, R.J. *Robust Model-Based Fault Diagnosis for Dynamic Systems*. Kluwer Academic Publishers, 1999.

[4] Golan, O. and Idan, M. and Meir, R. A non model based analytical detection of an abrupt change fault in flight control systems. In *40-th Israel Annual Conference on Aerospace Sciences*, Tel-Aviv/Haif, Israel, February 23–24, 2000.

[5] S. Haykin. *Neural Networks: A Comprehensive Foundation*. Prentice Hall, New Jersey, second edition, 1999.