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Model-Based Fault Diagnosis for Aerospace Systems

Nikunjun Sarker Akash[1], Xue Hongjun[1,2], Mahabub Sultan[3] and Nazmul Hasan Anik Chawdhury[4]*

[1]School of Aeronautics, Northwestern Polytechnical University, Xi'an 710021, China

[2]Shenzhen Research Institute, Northwestern Polytechnical University, Shenzhen 518057, China

[3]Buffalo State University, Buffalo, NY 14212, USA

[4]Aviation and Aerospace University Bangladesh, Lalmonirhat Sadar, Lalmonirhat, Bangladesh

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Author : Mahabub Sultan

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***Correspondence:**
Mahabub Sultan, SUNY Buffalo State University, Buffalo, New York, United States,
E-mail: mahabubsultan2@gmail.com

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Abstract

This review of model-construct blame determination centers in light of those strategies that are relevant to aviation frameworks. To feature the qualities of aviation models, nonexclusive nonlinear dynamical displaying from flight mechanics is reviewed and a binding together portrayal of sensor and actuator shortcomings is displayed. A broad bibliographical audit underpins a portrayal of the key purposes of blame identification strategies that depend on explanatory repetition. The approaches that best suit the imperatives of the field are underscored and proposals for future improvements in-flight blame determination are given.

Keywords: Aerospace Systems; Aircraft; Analytical Redundancy; Fault Diagnosis; Fault Detection and Isolation; Flight Control Systems; Health Monitoring; Non-Linear Systems

Introduction

Many methods have been proposed to address model-based fault diagnosis, an overview of which can be obtained from reference textbooks and survey papers. Papers are sorted according to the type of vehicle considered and a classification is proposed relating the fault diagnosis methods employed to each category of aerospace model. Common mathematical modelling of flight dynamics is also recalled, as it is the basis of dynamical models for fault diagnosis. Sections associates fault detection methods with their aerospace applications.

Specialists in aerospace engineering will access a self-contained overview of applicable Fault Detection and Isolation (FDI) methods through sections, while specialists in FDI looking for applications and benchmarks will find a generic modelling of aerospace systems and faults affecting their devices.

According to a reliability study conducted by the US Office of the Secretary of Defense, about 80 per cent of flight incidents concerning Unmanned Aerial Vehicles (UAV) are due to faults affecting propulsion, flight control surfaces, or sensors.

Classically, hardware redundancy – multiple sensors or actuators with the same function – and simple three holding were used to address fault detection. Emphasis will be put in this article on those model-based quantitative methods that have been used for aerospace applications. Common mathematical modelling of flight dynamics is also recalled, as it is the basis of dynamical models for fault diagnosis. Finally, this presentation may facilitate interaction between users of different FDI approaches on various flight systems.

Basics of FDI

Terminology

Fault detection is the determination of the presence of faults in a system and of their times of occurrence. It is generally followed by fault isolation to determine the type and location of the faults. These tasks generally involve the generation of residuals, which are fault indicators based on deviation between measurements and modelbased computations. Residuals should remain small as long as there is no fault, and become sufficiently large to be noticeable whenever faults occur.

Types of faults

Three types of faults are generally distinguished, according to the part of the system they affect.

1. A sensor fault is an abnormal variation in measurements, e.g. a systematic error abruptly

affecting the value provided by an accelerometer.

2. An actuator fault is a malfunction on a device acting on the system dynamics, e.g. the locking in-place of a flight control surface.

3. Process faults are changes in the inner parameters of the system that modify its dynamics, such as an unmodelled change in aerodynamic coefficients.

Architecture of model-based methods

Fault diagnosis is typically achieved by combining a residual generator and a residual evaluation strategy to provide Boolean decisions on whether faults have occurred. Residual generation uses a model of the system in which the control inputs sent to the actuators and the system outputs as measured by the sensors are injected to predict the behavior of the system (or part of it) and compare this prediction to the actual behavior. The residuals should be close to zero in fault-free condition and deviate from zero after the occurrence of faults to which they are sensitive. This generally involves the choice of thresholds or tests of statistical hypotheses.

FDI performance and robustness issues

An adequate tuning of an FDI procedure should lead to a satisfactory trade-off between the contradictory objectives of minimizing the rates of non-detection (missing a fault) and false-alarm (raising an alarm in fault-free condition). Assuming that the fault is persistent, one can define the following indices to evaluate faultdetection performance.

Aerospace Models for FDI

Fault Detection, Isolation, and Recovery (FDIR) is a subfield of control engineering which concerns itself with monitoring a system, identifying when a fault has occurred, and pinpointing the type of fault and its location. Two approaches can be distinguished: A direct pattern recognition of sensor readings that indicate a fault and an analysis of the discrepancy between the sensor readings and expected values, derived from some model. In the latter case, it is typical that a fault is said to be detected if the discrepancy or residual goes above a certain threshold. It is then the task of fault isolation to categorize the type of fault and its location in the machinery. Fault Detection and Isolation (FDI) techniques can be broadly classified into two categories. These include model-based FDI and signal processing based FDI.

Model based FDI

In model-based FDI techniques some model of the system is used to decide about the occurrence of fault. The system model may be mathematical or knowledge based. Some of the model-based FDI techniques include observer-based approach, parityspace approach, and parameter identification based methods. There is another trend of model-based FDI schemes, which is called set-membership methods. These methods guarantee the detection of fault under certain conditions. The main difference is that instead of finding the most likely model, these techniques omit the models, which are not compatible with data.

The example shown in the figure on the right illustrates a model-based FDI technique for an aircraft elevator reactive controller through the use of a truth table and a state chart. The truth table defines how the controller reacts to detected faults, and the state chart defines how the controller switches between the different modes of operation (passive, active, standby, off, and isolated) of each actuator. For example, if a fault is detected in hydraulic system 1, then the truth table sends an event to the state chart that the left inner actuator should be turned off. One of the benefits of this model-based FDI technique is that this reactive controller can also be connected to a continuous-time model of the actuator hydraulics, allowing the study of switching transients.

Flight mechanics and mathematical modelling

The unbending movement of a flight vehicle is for the most part parametrized in two casings, to be specific the route and body outlines. The route outline is appended to a settled area at Earth's nearby digression plane and oriented, e.g. north - east - down. It is then thought to be a nearby inertial edge where Newton's laws of movement apply. The body outline has its beginning at the focal point of mass of the air ship and its tomahawks are, separately oriented forward along the longitudinal hub, to one side along the sidelong pivot and descending.

Kinematics of Moving Frames

An understanding of inertial guidance systems for navigation of vehicles and robots requires some background in kinematics. Central in our discussion is the use of multiple reference frames. Such frames surround us in our daily lives:

- Earth latitude and longitude
- Forward, backward motion relative to current position
- Right, left motion
- Axes printed on an inertial measurement unit
- Vehicle-referenced coordinates, e.g.,

Relative to the centroid we first describe how to transform vectors through changes in reference frame. Considering differential rotations over differential time elements gives rise to the concept of the rotation vector, which is used in deriving inertial dynamics in a moving body frame.

We denote through a subscript the specific reference system of a vector. Let a vector expressed in the inertial (Earth) frame be denoted as vector x, and in a body-reference frame vector xb. For the moment, we assume that the origins of these frames are coincident, but that the body frame has a different angular orientation. The angular orientation has several well-known descriptions, including the Euler angles and the Euler parameters (quaternions). The former method involves successive rotations about the principal axes, and has a solid link with the intuitive notions of roll, pitch, and yaw. One of the problems with Euler angles, however, is that for certain specific values the transformation exhibits discontinuities (as will be seen below). Quaternions present a more elegant and robust method, but with more abstraction. We will develop the equations of motion here using Euler angles.

Faults on sensors and actuators

Smart structures can be used for Active Vibration Control (AVC) and also for Structural Health Monitoring (SHM). In such cases it is desirable that the instrumentation involved is reliable and any faults must be detected and isolated as soon as possible. In this work, some Fault Detection and Isolation (FDI) approaches applied to SHM and AVC systems were evaluated. The structure used for tests was a cantilever beam instrumented with two sensors and two actuators, all piezoelectric elements. Output observers and filters were used to conduct fault detection. They provide estimates of the measured outputs. The subtraction between measured and estimated quantities provides a signal called residue, which should be small in the absence and large in the presence of fault. These output observers/filters can be designed in various ways and the following approaches were considered: state observer, Kalman filter and H-infinity filter. In addition to know if a fault occurred, it is also necessary to determine in which element of the system the fault is present and under which severity. For this, the strategy adopted was to use a bank of observers where each component is an Output observer designed taking into account a system with only a specific fault. This scheme can be interpreted as a matrix, where each line refers to a certain severity and each column to one of the monitored instruments. Thus, the plant output is compared with the estimated output for each of the observers, giving rise to various signs of residue.

Within each column of the bank, the smallest amount of residue indicates the degree of degradation of the instrument. So the faults are isolated. The severity of these faults can be determined by some indicators. Among a myriad of possibilities, three indicators were used: Root Mean Square Difference, Sum of the Modulus of the Error and Modal Assurance Criterion. These indicators were applied to the residue supplied by each component of bank of observers. Computational tests were performed on a beam modeled by finite element method, initially without controller (SHM system) and after in the presence of an H-infinity controller (AVC system). Disturbances, measurement noises, modeling uncertainties and simultaneous faults were considered.

Methods for FDI

When no explicit dynamical model is available, system knowledge boils down to realtime measurements, possibly completed by process history. With such data, two main strategies may be adopted. The first strategy is classification, which involves building classes from the database either in a supervised way (i.e. with the help of an expert) or in a semi supervised manner (i.e. putting in the same class elements of the database that are deemed close to one another, and relying on an expert only to label the classes). A classifier is then trained with respect to these classes to assign the newly measured variables to classes' representative of healthy or faulty behaviors. The second strategy is regression, which builds a statistical model that uses redundancy in the process history to predict the values of variables and generate residuals by comparing predictions to measured values.

Model free methods of FDI

In-flight securement of aircrafts can be performed either by completing on-board equipment with additional measurement devices or by means of algorithmic procedures exploiting the available measurements. In this paper, we aim at identifying early unexpected changes (faults) in an aerial system before they lead to a complete breakdown (failure), without adding sensors. This objective should be fulfilled by applying Fault Detection and Isolation (FDI) methods to a class of aerial systems with typical sensors and actuators. The set of devices is fixed and no hardware redundancy is allowed. A nonlinear knowledge-based dynamical model of the vehicle in statespace form is also available, but will only be used to design the control law.

FDI for aerial and space vehicles have already been addressed in many papers (see, e.g., Patton (1991)). Most of the work of the diagnosis community has been focused on linear systems but recently there has been some trend toward fault detection methods for nonlinear systems (see, e.g., Witczak (2007)). In Marzat et al. (2009), a survey of the main FDI methods is presented, where both modelfree and model-based methods are described and the most promising approaches for the aircraft securement problem in question are shortlisted. However, all these approach.

Parameter Estimation

The term parameter estimation refers to the process of using sample data (in reliability engineering, usually times-to-failure or success data) to estimate the parameters of the selected distribution. Several parameter estimation methods are available. This section presents an overview of the available methods used in life data analysis. More specifically, we start with the relatively simple method of Probability Plotting and continue with the more sophisticated methods of Rank Regression (or Least Squares), Maximum Likelihood Estimation and Bayesian Estimation Methods.

State Estimation

In this section, we study the Kalman filter. First we state the problem and its solution. In particular, we discuss some of the senses in which the Kalman filter is optimal. After that, we give a relatively straightforward proof of the Kalman filter.

Residual Evaluation

After residuals - presumably noisy and disturbed have been generated by methods from section 4, there is the need to analyse them on-line to provide Boolean decisions on whether they significantly differ from those that would be generated during normal operation. Given this collection of Boolean values, the fault-incidence matrix should be built, to express the influence of each fault on residuals [303, 304]. To achieve isolation, each fault should affect a different set of residuals – this is, e.g. what is seeked for by DOS and GOS architectures.

Sequential probability ratio test

The sequential probability ratio test is very similar to the generalized likelihood ratio, as it also uses the likelihood ratio. However, the minimum size of changes to be detected 1 has to be specified, and the threshold is fully determined by fixing the desired false-ala.

Conclusions

Papers in this format must not exceed twenty (20) pages in length. Papers should be submitted to the secretary AIRCC. Papers for initial consideration may be submitted in either .doc or .pdf format. Final, camera-ready versions should take into account referees' suggested amendments.

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