FAULT DETECTION AND IDENTIFICATION OF ACTUATOR FAULTS USING LINEAR PARAMETER VARYING MODELS

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Abstract: A method is proposed to detect and identify two common classes of actuator faults in nonlinear systems. The two fault classes are total and partial actuator faults. This is accomplished by representing the nonlinear system by a Linear Parameter Varying (LPV) model, which is derived from experimental input-output data. The LPV model is used in a Kalman filter to estimate augmented states, which are directly related to the faults. Decision logic has been developed to determine the fault class from the estimated augmented states. The proposed method has been validated on a nonlinear simulation model of a small commercial aircraft.

Keywords: Fault detection and identification, LPV models, Aircraft control, Nonlinear systems

1. INTRODUCTION

Due to the increased demand of reliability of systems, the field of Fault Detection and Identification (FDI) using analytical redundancy has attracted the interest of many researchers. Different views originated which have resulted in different FDI methods such as the parity space approach, parameter estimation methods and principal component analysis. A thorough discussion of these methods can be found in Chen and Patton (1999) and Blanke *et al.* (2003).

However, the majority of classic FDI research is focused on linear systems, whereas many practical systems show a strongly nonlinear behavior. Hence, more recently nonlinear FDI has become a topic of interest. Some results have been obtained using nonlinear system theory, see e.g. Persis and Isidori (2001). These results however require that the nonlinear model is simulated in realtime with the system to be monitored. For complex systems this can be impossible due to the limited computation power in practical applications. Furthermore, theoretical derivations of stability and performance can become very involved for these complex systems. Therefore, another approach is to use LPV systems to model the nonlinear systems. The main advantage of LPV models is that powerful linear design tools can be applied to complex nonlinear models. LPV models have already been used frequently for control purpose, e.g. in aircraft (Balas, 2002). However, the application of LPV methods to FDI has not been fully exploited yet. One of the very few research efforts on the application of LPV models to FDI can be found in Bokor and Balas (2004). Here, the geometric approach for linear FDI is extended to LPV systems. In this paper we will also pursue the LPV FDI philosophy, but with another approach for FDI.

In most current aircraft, FDI is based on redundant hardware. However, this form of redundancy has some disadvantages such as the costs for the extra hardware, the increased weight and maintenance. Therefore, this research, which was performed in the scope of the European ADFCS-II project focuses on using analytical redundancy methods for actuator faults in aircraft. The FDI approach used here, is the parameter estimation approach. In this approach, parameters which are directly related to actuator faults such as multiplication factors on inputs and measurements, will be estimated together with the system state. The resulting filter is referred to as an augmented filter. This FDI approach has proven its usefulness in Gobbo *et al.* (2001) in which an extended Kalman filter, which linearizes the nonlinear model each time step, is applied to FDI. This linearization at each time step can be very time inefficient for large systems. Furthermore, the same method has been used in Mešić *et al.* (2003) in which a linear model is used. The main contribution of this paper is the use of the augmented filter approach for FDI in combination with LPV models, instead of linear models or models linearized at each step of the filter.

This paper is organized as follows. In section 2 the augmented filter will be described together with the decision logic. Section 3 will deal with the LPV model that is used for FDI. In section 4 an evaluation of the proposed method will be given. Section 5 is devoted to the conclusions.

2. ACTUATOR FDI WITH AUGMENTED FILTERS

In Figure 1 an overview is given of a control system that is equipped with FDI. In such a system, faults can occur in the actuators, sensors and in the components of the system itself (e.g. wing damage of an aircraft). In this paper we will focus only on actuator faults. These actuator faults will be identified by analyzing the difference between the two signals u_c and u_s in the figure. The signal u_s is not measurable. Instead, it is estimated by using an analytical model of the system. In case of a fault, the command signal from the controller u_c, is not equal to the input signal that really excites the system u_s. In the nominal (fault free) case it holds that $u_c = u_s$. In order to detect and identify a fault, the following parametrization of the state-space model is used

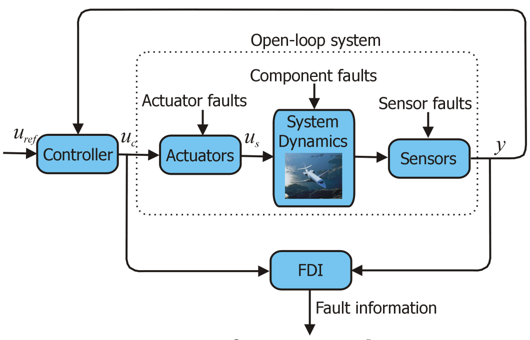

Fig. 1. An overview of a monitored system.

$$x(k+1) = Ax(k) + B\Big(\beta(k) * u_c(k)\Big) + w(k) \quad (1)$$

$$y(k) = Cx(k) + D\Big(\beta(k) * u_c(k)\Big) + v(k) \quad (2)$$

where $*$ is a point-wise multiplication, $x(k) \in \mathbb{R}^n$ is the state, $u_c(k) \in \mathbb{R}^m$ is the input, $y(k) \in \mathbb{R}^l$ is the output and $w(k)$ and $v(k)$ are respectively the process noise and the measurement noise. These noises are assumed to be zero mean white noise sequences with covariance matrices Q and R, defined by

$$E\begin{bmatrix} v(k) \\ w(k) \end{bmatrix} \begin{bmatrix} v(j)^T & w(j)^T \end{bmatrix} = \begin{bmatrix} R(k) & S(k)^T \\ S(k) & Q(k) \end{bmatrix} \delta(k-j), \quad (3)$$

where $\delta(j)$ is the unit pulse, E is the expectation operator, and $R(k)$ and $Q(k)$ are both positive definite. The multiplication factor $\beta(k) \in \mathbb{R}^m$ is the parameter that will reflect the fault. So, in order to know whether a fault has occurred, this parameter is estimated from the following augmented system

$$\hat{x}_a(k+1) = \begin{bmatrix} A & B_u(k) \\ 0 & I \end{bmatrix} \hat{x}_a(k) + w_a(k) \quad (4)$$

$$\hat{y}(k) = \begin{bmatrix} C & 0 \end{bmatrix} \hat{x}_a(k) + D\Big(u_c(k) * \hat{\beta}(k)\Big) + v(k) \quad (5)$$

where $\hat{x}_a(k) = \begin{bmatrix} \hat{x}(k) & \hat{\beta}(k) \end{bmatrix}^T$ is the total state estimated by the augmented filter. The term B_u is a short notation for $[B_1 u_{c1}(k) \quad \ldots \quad B_m u_{cm}(k)]$, where B_i represents the i-th column of B and $u_{ci}(k)$ represents the i-th component of $u_c(k)$. The process noise now becomes $w_a(k) = [w(k) \;\; w_\beta(k)]^T$. In this formulation the fault parameter $\beta(k)$ is assumed to evolve as a random walk (Brownian motion). Random walk is the integration of white noise. Although it is unknown how the fault parameter $\beta(k)$ will exactly evolve, the random walk assumption has proven to model such signals sufficiently well (Mešić *et al.*, 2003). By using the random walk model variation of the uncertainty and the rate at which it changes can be reflected. Tuning of $w_\beta(k)$ determines the behavior of $\hat{\beta}(k)$. The relation between $u_c(k)$ and $u_s(k)$ is

$$u_s(k) = u_c(k) * \hat{\beta}(k) \quad (6)$$

The observer used to estimate the augmented state is the Kalman filter. Tuning of the Kalman filter is done by changing the parameters of the the covariance matrices Q_a of the augmented state $x_a(k)$ and R. Section 4 will elaborate further on the tuning process.

2.1 *Types of actuator faults*

Common actuator faults in aircraft can be subdivided into two types (Bošković and Mehra, 1999): total faults and partial faults. When a total fault takes place in an actuator, the actuator does not react on the control signals anymore. When a partial fault occurs, the actuator still reacts on the control signal, but with decreased efficiency. In Figure 2(a) two types of total actuator faults are depicted. A fault is called “lock-in-place” if the actuator remains at the position it was at the beginning of the fault. A fault is called “hard-over” if the actuator goes to its maximum or minimum limit after the fault. Furthermore it can be seen in this

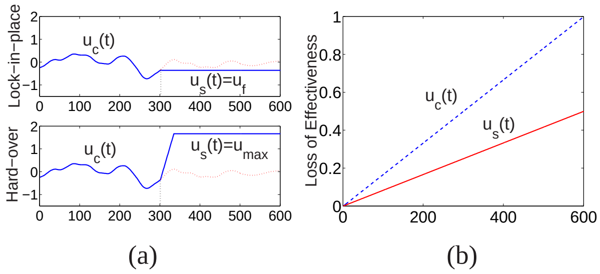

Fig. 2. Types of actuator faults.

figure that although the control signal $u_c(t)$ (dotted line) still varies after the fault occurs at T=300, the control signal by which the aircraft is excited $u_s(t)$ remains constant (solid line). In Figure 2(b) a partial fault of 50% is depicted. It can be seen that the control signal $u_c(t)$ is multiplied by a factor of 0.5 before it excites the system as $u_s(t)$.

2.2 *Decision logic*

In order to determine what type of fault occurred and at what time, the output of the augmented filter $\hat{\beta}(k)$ is processed by decision logic. First, a fault has to be detected. This is done by detecting changes in the fault parameter $\hat{\beta}(k)$, which will deviate from its nominal value of 1 when a fault occurs. The implemented change detection algorithm is the two-sided cumulative sum (CUSUM) algorithm (Basseville and Nikiforov, 1993).

After a change has been detected the fault type must be determined. Is it a total or a partial fault? In order to answer this question, an analysis of the numerical derivative of the reconstructed signal $\Delta u_s(k) = u_s(k) - u_s(k-1)$ is made. If $\Delta u_s(k)$ is not close to zero after the fault has been detected, we may conclude that a partial fault has occurred. Otherwise, it is concluded that the fault is total because for total faults $u_s(k)$ remains constant. However, in practice it is difficult to make the right decision about the fault type by passively analyzing $\Delta u_s(k)$. The reason for this is the fact that an aircraft may not be excited enough just after the fault has occurred. Therefore, the choice has been made to use an extra excitation signal directly after the detection of the fault. This excitation signal should be designed such that it gives enough excitation and that the extra dynamics are within the comfort and safety requirements of the system. An extensive description of the design of such signals is given by Campbell and Nikoukhah (2004).

In Table 1, the fault status resulting from the chosen decision logic is given. The fault status can remain 1 during the whole period of extra excitation, if no significant change in $\Delta u_s(k)$ is detected. At the end of the excitation signal, the fault status then becomes 3. In case of a total fault, the fault type can either be a hard-over or lock-in-place type of fault. The only difference is that a hard-over has a constant $u_s(k)$ at the upper or lower saturation limit.

Table 1. Description of the fault status.

Fault status	Description
0	No fault detected
1	Fault detected, but not yet identified
2	Fault is partial
3	Fault is total

3. AN LPV MODEL FOR FDI

If a model of a nonlinear system is linearized at a certain operating point, the obtained linear model looses its validity when the system goes to other operating points. Because this model mismatch can easily be mistaken for a fault by the FDI system, using only one linear model is not suitable for performing FDI of the system in its whole operating regime. For this reason, LPV models are used to model the system. The most general form of an LPV model is given by

$$x(k+1) = A(\rho(k))x(k) + B(\rho(k))u(k) \quad (7)$$
$$y(k) = C(\rho(k))x(k) + D(\rho(k))u(k) \quad (8)$$

Note that although the LPV model has a structure resembling that of a linear model, the system matrices are now dependent on a parameter vector $\rho(k)$. This "linear" structure allows the use of "linear" design methods, and at the same time, the LPV model is able to represent the nonlinear model in a larger part of the operating region than a linear model. Thanks to these advantages, LPV systems have attracted an increasing interest from the academic research community the last ten years (Rugh and Shamma, 2000).

3.1 *Identification of LPV models*

There are different ways to obtain LPV models. There are methods which use the nonlinear equations of the system to derive an LPV model such as state transformation, function substitution and methods using Jacobian linearization (Marcos and Balas, 2004). There are also methods using only input/output data to obtain an LPV model. In this paper, one of the latter methods is chosen. The assumption has been made that the exact nonlinear model is not known and that only input/output data are present. For real systems this is often the case, although the model structure might be known, the exact values of the model parameters still have to be estimated. From the input/output data an LPV state-space model is identified using LPV subspace identification techniques. In order to further improve the performance of the identified LPV model, this model is used in Verdult *et al.* (2003) as an initial estimate for the minimization of the output-error cost function

$$V_N(\theta, \rho) = \sum_{k=1}^{N} \|y(k) - \hat{y}(k; \theta, \rho)\|_2^2 \quad (9)$$

where $y(k)$ is the output of the real system, $\hat{y}(k; \theta, \rho)$ is the output of the model as a function of the full parametrization of the system matrices θ and the scheduling parameters ρ. The total number of measurements is indicated by N. Because this optimization process is both nonlinear and nonconvex, a projected gradient search method has been used to solve it. The LPV models that can be identified with the described procedure have the form

$$x(k+1) = \Big(A_0 + \sum_{i=1}^{s} A_i \rho_i(k)\Big) x(k) + \Big(B_0 + \sum_{i=1}^{s} B_i \rho_i(k)\Big) u(k) \tag{10}$$

$$y(k) = \Big(C_0 + \sum_{i=1}^{s} C_i \rho_i(k)\Big) x(k) + \Big(D_0 + \sum_{i=1}^{s} D_i \rho_i(k)\Big) u(k) \tag{11}$$

where s is the number of scheduling parameters $\rho(k) \in \mathbb{R}$. This particular type of LPV model has been referred to as parameter dependent system (PDS) in Gahinet *et al.* (1995).

3.2 *Identification of an LPV aircraft model*

In this paper, an LPV model of a small commercial aircraft has been identified using input/output data of a nonlinear simulation model of this aircraft. Only the longitudinal dynamics of the aircraft are considered. The identified LPV model of the aircraft is of second order and it uses three scheduling parameters. In Table 2, the structure of this model is given.

Table 2. Structure of the identified LPV model.

Inputs ($u(k)$)	**Outputs** ($y(k)$)	**Scheduling Parameters** ($\rho(k)$)
Elevator	Pitch rate	True Airspeed
Throttle	Angle of attack	Dynamic Pressure
	Downward speed	Flight-path Angle
	Hor. acceleration	

The aircraft is excited in open-loop by input signals taken from a maneuver of the aircraft performed by the autopilot without faults. In this way, the open loop simulation of the aircraft approaches the trajectory flown in closed loop. Choosing the scheduling parameters $\rho(k)$ properly is very important to obtain a good LPV model for FDI. These parameters determine how an LPV model behaves throughout its operating region. The scheduling parameters are chosen on the basis of experimentation with different combinations of common scheduling parameters in the literature, see e.g. Marcos and Balas (2004) and Szászi *et al.* (2002). The identified LPV model identified is valid for a limited part of the operating region.

It is made sure that the quality of the model is high for the maneuver without faults. The quality of the model is measured using the Variance Accounted For (VAF) for a data set that is different from the one used for identification. The VAF is defined as

$$\text{VAF} = \max\left\{1 - \frac{\text{var}(y(k) - \hat{y}(k))}{\text{var}(y(k))}, 0\right\} \times 100\% \tag{12}$$

where $\hat{y}(k)$ denotes the output signal from the simulation of the LPV model and $y(k)$ is the output of the nonlinear simulation and var$(\cdot)$ denotes the variance of the signal. The VAF for the model used in the simulation in the fault-free case in section 4 is $[83.87\ \ 90.89\ \ 93.86\ \ 97.28]^T$.

4. EVALUATION OF THE PROPOSED METHOD

The proposed LPV FDI method has been tested on a nonlinear closed loop simulation of a small commercial aircraft. Only the primary controls of the longitudinal model were considered. These controls are the elevator and the throttle. The faults were simulated by manipulating the control outputs of the autopilot of the aircraft. There is no reconfiguration strategy implemented yet. This means that when a fault occurs, the controller will change the control command to still reach its objective. Two faults have been simulated on the elevator; one partial and one total fault.

In the simulations, not only the results of LPV FDI are considered, but also the results obtained with a Linear Time Invariant (LTI) model. This has been done to display that an LTI model is not sufficient for FDI in the performed experiments. The LTI model used for this purpose, which is of fourth order, is obtained by trimming and linearization of the nonlinear aircraft model at the initial conditions of the experiments (Pull-up trim with MACH =0.4, Altitude=17Kft, Flight-path Angle=7°). It may therefore be considered as a very accurate representation of the nonlinear aircraft at the initial conditions.

Tuning of the proposed FDI system as a whole can be done in both the augmented filter and the decision logic. The tuning process of the decision logic involves choosing the sensitivity parameters of the CUSUM detector. The tuning process of the augmented filter involves choosing covariances for the process (states) and the measurements in the Q_a and R matrix, respectively. For example, if a certain measurement is more important than another one then its covariance should be chosen smaller. In this way the important measurement has a greater impact on the estimation. The assumption has been made that the measurements and the states are not correlated with themselves and each other. This assumption allows the matrices Q_a and R to be diagonal matrices and the matrix S (from equation 3) to be zero. The LPV filter has been implemented in the same way as the LTI filter, with the difference that the LPV filter has varying system matrices. Furthermore, the two filters are tuned differently because of the different model structure.

4.1 Partial fault on the elevator

In this experiment a partial fault is inserted in the elevator during a pull-up maneuver of the aircraft. In order to to clarify the flight condition during the experiment the scheduling parameters during the experiment are depicted in Figure 3. The simulated fault is an

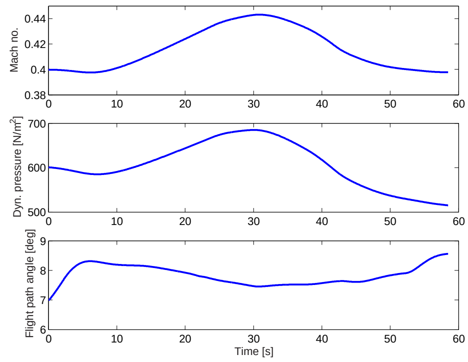

Fig. 3. Evolution of the scheduling parameters throughout the experiment

incipient loss of effectiveness from 1 to 0.5, it starts at T=20s and ends at T=30s with an effectiveness of 0.5. The results of this experiment are depicted in Figures 4 and 5. Figure 4 shows the estimated fault parameters

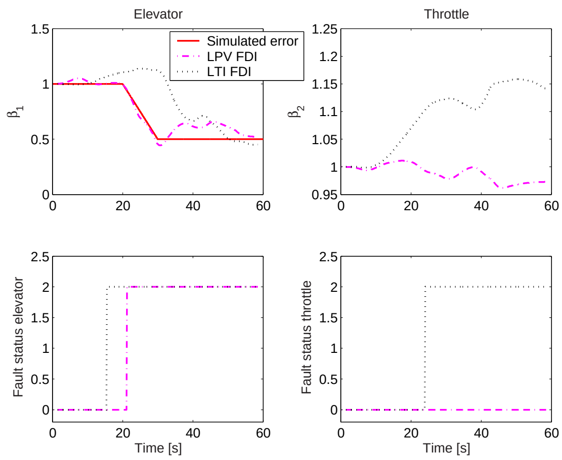

Fig. 4. Fault parameters and fault status with the LTI and LPV FDI approach for a partial fault.

($\hat{\beta}(k)$) and the fault status of the two controls of the aircraft. The left column corresponds with the elevator and the right column corresponds with the throttle. In the upper left part of Figure 4 the simulated fault on the elevator is also depicted. It can be seen that the fault parameter estimated by the LPV FDI filter follows the simulated fault much more closely than the LTI filter. Furthermore, it can be seen that the LTI FDI filter also shows a significant variation in the fault parameter of the throttle. This highly undesirable result is caused by the model mismatch. In the fault status plots of the two controls it can be seen that in the LTI case two wrong decisions are made: one is the fault in in the throttle and one is the fault in the elevator which

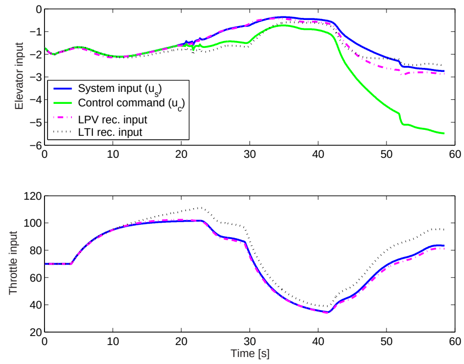

Fig. 5. Reconstructed inputs for the LTI and LPV FDI approach for a partial fault.

is issued too early. Both these fault notifications are thus false alarms. The partial fault which was issued at T=20s is correctly identified by the LPV FDI filter at T=21.12s. In Figure 5 the reconstructed inputs of the two filters (computed with equation 6) together with the control command u_c and the real system input u_s for the elevator and the throttle are given. u_s and u_c are of course equal until the fault occurs. In this figure it can be seen more clearly that the reconstructed input from the LPV FDI filter follows the simulated u_s much better. Furthermore, the excitation signal can be clearly seen immediately after T=21.12s.

4.2 Total fault on the elevator

In this experiment a total fault on the elevator is simulated also during pull up of the aircraft. The initial conditions are the same as for the first experiment. In this case a "lock-in-place" fault is simulated at an elevator deflection of -1.5° at T=43.1s. This can be clearly seen in Figure 7. This time, the simulated fault is not a multiplication of the control command u_c and therefore it is not depicted in the upper left part of Figure 6 as it was the case with the first fault. The rest of the results, however, are presented exactly on the same manner as for the first fault. In Figure 6 it can be seen that the LTI FDI filter again makes two wrong decisions. In Figure 7 it can be seen that the LPV FDI filter follows the system input more closely than the other filter. In this figure it can also be seen that u_c gets out of the range of the figure because the controller attempts to control the aircraft anyway. Furthermore, it can be seen that the LPV FDI input follows the control command just after the fault between 43s and 46s. This is the result of the tuning process. If the filter is tuned to react on very fast changes of the control command when a fault occurs, the filter would be unsuitable for the normal case because of its jumpy nature (which would cause many false alarms). Therefore this trade-off has been made. Now, the total fault is correctly detected by the LPV FDI filter at T=44s.

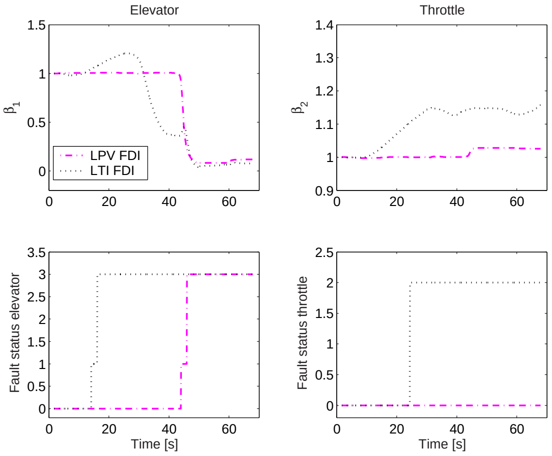

Fig. 6. Fault parameters and fault status with the LTI and LPV FDI approach for a total fault.

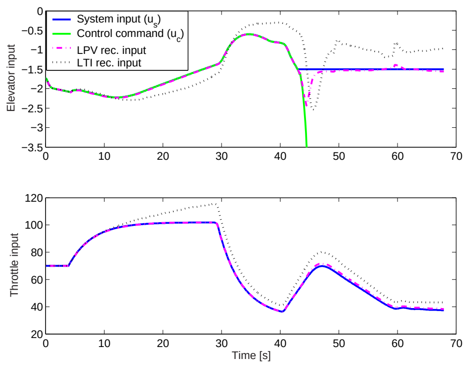

Fig. 7. Reconstructed inputs for the LTI and LPV FDI approach for a total fault.

5. CONCLUSIONS

A fault detection and identification (FDI) method was presented to identify both total and partial actuator faults in nonlinear systems. The FDI method uses an augmented Kalman filter to estimate fault related parameters. In order to deal with the nonlinearity of the model an LPV model of the system has been used. This LPV model has been identified from input/output data of the system. The proposed method has proven its effectiveness in two simulations of a nonlinear aircraft model. A partial fault and a total fault were simulated. The LPV FDI filter was able to quickly and correctly identify the two faults. Also an LTI FDI augmented filter was implemented to display that it is not sufficient to achieve the desired goal. Currently, the LPV model is only valid in a limited part of the operating region of the aircraft. Future research will focus on expanding the operating region of the augmented filter. Furthermore, also sensor faults and component faults will be taken into account.

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