A FUZZY LOGIC – PARITY SPACE APPROACH TO ACTUATOR FAILURE DETECTION AND IDENTIFICATION

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Abstract

The integration of fuzzy logic and parity space methodologies is explored for the detection and identification problem of actuator failures of aircraft. Actuator failures are identified in magnitude as bias and scale factor changes. The nonlinear fuzzy logic-parity space approach performs accurately over varied flight conditions. The estimated (fuzzy) failure status can directly be used to reconfigure the control system smoothly. The concepts are demonstrated by a simulation example of a nonlinear, six degree-of-freedom civil aircraft model under realistic conditions.

1. Introduction

Timely detection and identification of flight control system failures is critical to the safety of aircraft. Among many possible failures, sensor and actuator failures have a direct impact on the performance of the control system. Physical (or parallel) redundancy, obtained by implementing two, three, or more different components with the same function, allows for a fast detection, identification, and accommodation of a failure. However, this may not be a practical approach for actuators, like control surfaces, that are not easily replicated. Actuator failures can be detected and identified by the inherent (analytical) redundancy contained in the static and dynamic relationships among the actuator commands and measured outputs, as described in this paper.

Examples of engine failures that had dramatic impact are the DC-10 crash at Chicago Airport in 1979,14 the B-747 crash at a suburban area of Amsterdam in 1992,26, and the B-767 accident near Bangkok in 1991. In the first and second accidents, engines broke off the wing, leading to loss of control. In the third case, one thrust reverser was deployed during cruising flight. An example of disfunctioning control surfaces is a left elevator, jammed in the “up” position of the L-1011 incident in 1977.7 The pilot was able to recover and land the aircraft by differential engine settings. In all cases, proper failure detection and identification might have helped to reconfigure the control system of the aircraft.

The first step towards failure accommodation is failure detection, referring to the detection of nominal operation. The usual approach is to compare measured and predicted outputs of the system by linear observers.16,13,25,35 Using a special type of open-loop, dead-beat observer, error indicators (residuals) can be defined such that they are nonzero only in case of failures. The set of residuals is generated by a parity-vector, which belongs to the so-called parity space.4,5,6,8,20,26,27 The next step is the identification of the failure, referring to the classification of the type (scaling, bias), and magnitude of the failure. The usual approach is formulating a specific test, such as the multiple-model hypothesis test.35 Each failure hypothesis is modeled by a separate observer, and the most likely hypothesis indicates the failure.2,22 Hypothesis tests get complex and computationally intensive when failure type as well as magnitude are needed for reconfiguration. Finally, after detection and identification of
2. Nonlinear failure detection

Linear parity equations

Failure detection is based on a set of residuals that are non-zero only when failures occur. Each residual should be influenced by just one actuator, making isolation of the failure possible. A well-known approach to failure detection is the so-called parity space approach. The main idea of the parity space approach is to check the consistency (parity) of the mathematical equations of the system by using the actual measurements. There are direct and temporal analytical redundancy relations, referring to static relationships among instantaneous sensor outputs, and dynamic relationships between sensor outputs and actuator inputs, respectively. Since only actuator failures are considered in this paper, temporal relations are used.

Consider a nonlinear system, for which small perturbations \( \Delta \) around an operating point are modeled by the linear, time-invariant, discrete-time state equations:

\[
\begin{align*}
\Delta x(k+1) &= A\Delta x(k) + B\Delta u(k) + F\Delta d(k) \\
\Delta y(k) &= C\Delta x(k) + D\Delta u(k) + G\Delta d(k),
\end{align*}
\]

with \( x = x_0 + \Delta x, \ u = u_0 + \Delta u, \ y = y_0 + \Delta y, \) and \( d = d_0 + \Delta d. \) The \( x \) is the \( n \times 1 \) state vector, \( u \) the \( p \times 1 \) actuator input vector, \( y \) the \( q \times 1 \) sensor output vector, \( d \) the \( r \times 1 \) disturbance vector, and \( A, B, C, D, F, \) and \( G \) are matrices of appropriate dimensions.

The redundancy relations for this linear model are specified mathematically as follows. First, define the subspace of \( (s+1)q \) dimensional vectors \( v \) by:

\[
P = \left\{ v | v^T \begin{bmatrix} C \\ CA \\ \vdots \\ CA^q \end{bmatrix} = 0 \right\}. \tag{2}
\]

This is called the parity space \( P \) of order \( s, \) with \( s \leq n. \) Every vector \( v \) can be used at any time \( k \) to form a parity equation:

\[
r(k) = v^T [\Delta Y(k) - H_1 \Delta U(k)], \tag{3}
\]

in which \( \Delta Y(k) = [\Delta y(k-s) \ldots \Delta y(k)]^T \) and \( \Delta U(k) = [\Delta u(k-s) \ldots \Delta u(k)]^T. \) The matrix \( H_1 \) is defined by:
The additional conditions define the parity space such that it also forms the orthogonal complement of the ranges of $H_2$ and $H_3$. Each residual is affected by just one input; the residual can be used as a direct indicator of a failure of the corresponding actuator. This is the ideal solution of finding proper residuals for each actuator. If one actuator fails, only the corresponding residual becomes nonzero. The magnitude of the residual corresponds with the magnitude of the failure, which will be shown in Section 3.

Remark. The residuals are affected by measurement noise. The input-to-noise ratio must be large enough for proper detection and isolation. In accordance with the parity equation (3), it is shown that each parity equation is, in fact, a form of dead-beat observer, where the difference between the measured and the predicted output is used to create the residual. This observer forms a special type of the so-called Unknown Input Observer (UIO), where all inputs except one and the disturbances are the unknown inputs. Formulating the observers as closed-loop observers, instead of open-loop, dead-beat observers, makes them more robust against noise, initial conditions, and modeling uncertainties. However, the straightforward relation between the magnitude of the failure and the magnitude of the residual is lost.

Nonlinear parity equations

The parity equations are based on linearized models describing the aircraft at one operating point. For varying flight conditions, linear residual generators are not appropriate. Therefore, a generalization of the linear approach is proposed using the so-called Takagi-Sugeno (TS) fuzzy models. For the principles of fuzzy sets and fuzzy logic the reader is referred to basic textbooks like [16].

Consider for example a residual generator that is defined for the $i$th operating point. If the aircraft is flying with a higher airspeed, the effectiveness of the control surfaces is higher, resulting in a significant change of the (linearized) aerodynamics. The conditions under which the corresponding residual $r_i$ holds, can be expressed as fuzzy propositions in an if-then rule, like:

\[
\text{If } z_1(k) \text{ is } S_{i1} \text{ and } z_2(k) \text{ is } S_{i2} \text{ and ... then output is } r_i(k).
\]

Here, $z = [z_1, z_2, \ldots]^T$ contains the antecedent variables (e.g., airspeed, mass, ...), $S_{ij}$ are the antecedent fuzzy sets, and $r_i(k)$ is the local linear residual. The fuzzy sets are defined by membership functions $\mu$ on $Z$ with $z \in Z$:

\[
\mu_{S_{ij}} : Z \rightarrow [0, 1].
\]
The membership functions are labelled by linguistic expressions like low, high etc. corresponding to the (flight) conditions. In the TS-model, all residuals contribute to the overall output, whereby each residual is weighted by the degree-of-fulfillment (truth value) of the corresponding rule. This indicates to what extent the local “model” is valid, according to the conditions under which the rule holds. The degree-of-fulfillment, denoted by \( \beta_i(z) \), is determined by fuzzy set operations. In this paper, the simple product operator is used for conjunction:

\[
\beta_i(z(k)) = \mu_{s_i1}(x_1(k)) \cdot \mu_{s_i2}(x_2(k)) \cdots \tag{10}
\]

Finally, the residual of the TS-model for one actuator is computed by a simple algebraic expression:

\[
r(k) = \frac{\sum_{i=1}^{m} \beta_i(z(k)) \cdot r_{i}(k)}{\sum_{i=1}^{m} \beta_i(z(k))}, \tag{11}
\]

with \( m \) being the number of local models.

In Figure 1, the TS-system is schematically shown. As a function of the system inputs and outputs, local residuals are calculated at each time step. Depending on the (flight) condition, the residuals are weighted and summed to give a single nonlinear residual for each actuator. For aircraft, the definition of fuzzy propositions is rather straightforward because of the clear physical interpretation. If the process under consideration is (partly) unknown, a fuzzy partitioning of the operating range can be found by identification techniques\(^3\). In both cases, a nonlinear residual generating system with a transparent structure is obtained.

![Fuzzy scheduling diagram](image)

Figure 1: Nonlinear residual generation using Takagi-Sugeno model.

By analyzing the TS-model, it can be shown that the TS approach is equivalent to scheduling the gains of just one residual generator. Let us denote the vector of past inputs and outputs of the nonlinear plant by:

\[
U(k) = [u_0(k) ... u_i(k)]^T, \quad Y(k) = [y_0(k) ... y_i(k)]^T
\]

and \( U_{0,i}(k) = [u_0(k) ... u_i(k)]^T, \quad Y_{0,i}(k) = [y_0(k) ... y_i(k)]^T \). Then equation (11) can be written as (the time step index \( k \) is omitted for convenience):

\[
r = \frac{\sum_{i=1}^{m} \beta_i(z) \cdot [v_i^T \Delta Y_i - H_{1,i} \Delta U_i]}{\sum_{i=1}^{m} \beta_i(z)}
\]

\[
= \sum_{i=1}^{m} \beta_i(z) \cdot \left[ \frac{v_i^T [(Y_{0,i} - Y_{i+1}) - H_{1,i}(U - U_{0,i})]}{\sum_{i=1}^{m} \beta_i(z)} \right]
\]

\[
= \left( \sum_{i=1}^{m} \beta_i(z) v_i^T \right) Y - \left( \sum_{i=1}^{m} \beta_i(z) v_i^T H_{1,i} \right) U
\]

\[
= \sum_{i=1}^{m} \beta_i(z) v_i^T Y_{0,i} - \sum_{i=1}^{m} \beta_i(z) v_i^T H_{1,i} U_{0,i}
\]

The above equation shows that the residual is obtained from observing the nonlinear system over a time window. The residual is calculated by scheduling the gains of just one parity equation that is simultaneously corrected by scheduled initial conditions.

### 3. Failure identification

#### Estimation of scaling and bias terms

From the magnitude of the residual \( r(k) \), the type and the magnitude of the failure has to be determined. Considering an arbitrary actuator, a simple failure model with a scaling (multiplicative) and a bias (additive) term can be described by:

\[
u(k) = \eta(k) \cdot u_c(k) + \lambda(k), \tag{14}
\]

where \( u(k) \) is the real actuator response, scaled by the factor \( \eta(k) \), and biased by the factor \( \lambda(k) \), and \( u_c(k) \) is the commanded input. In normal operation, \( \eta \) and \( \lambda \) are one and zero, respectively.

Since both parameters change in time, a recursive estimation procedure is formulated. Incorporating equation (14) into equation (13), and assuming that \( r(k) \) is zero under no failure conditions, yields:

\[
r(k) = \phi^T(k) \theta(k) + n(k) \tag{15}
\]

with \( \theta \), the parameter vector, \( \phi \), the regression vector, and \( n(k) \) representing the effect of measurement noise, non-decoupled disturbances, and modeling uncertainties. The two-dimensional parameter and regressor vectors are given by:

\[
\theta^T = [(1 - \eta(k)) \ -(\lambda(k))] \tag{16}
\]
\[ \phi^T(k) = \left[ \sum_{i=1}^{m} \beta_i(z(k))v_i^T H_{1,i} \right] U_c(k) \]
\[ \sum_{i=1}^{m} \beta_i(z(k))v_i^T H_{1,i} \right] \right]. \tag{17} \]

Estimating \( \hat{\theta} \) from equation (15) is a standard linear regression problem, which can be solved by the well-known recursive least squares (RLS) method. From equation (16), the scaling and bias estimates \( \hat{\eta}(k) \) and \( \hat{\lambda}(k) \) can be calculated.

Because of the unexpected character of the scaling and bias terms, the RLS method must be kept "alert". A straightforward way is to introduce a forgetting factor in the recursive equations, such that only the most recent observations are taken into account. However, in case of no input excitation (for example straight flight with no turbulence), the algorithm diverges because the most recent observations contain no information. A more formal solution of the problem is to consider the true parameter vector as a random variable:

\[ \theta(k+1) = \theta(k) + w(k), \tag{18} \]

where \( w(k) \) is a sequence of independent Gaussian random vectors such that \( w(k) \) has zero mean, and covariance matrix \( Q(k) \). The covariance matrix \( Q(k) \) is assumed to be known. Using equation (18) as the measurement equation, an optimal estimate for the parameter vector, \( \hat{\theta}(k) \), is obtained by means of a Kalman filter. The recursive equations are then given by:

\[ \hat{\theta}(k) = \hat{\theta}(k-1) + \]
\[ K(k) \left[ r(k) - \phi^T(k) \hat{\theta}(k-1) \right], \tag{19} \]
\[ K(k) = \frac{P(k-1)\phi(k)}{R(k) + \phi^T(k)P(k-1)\phi(k)}, \tag{20} \]
\[ P(k) = P(k-1) + Q(k) - K(k)\phi^T(k)P(k-1). \tag{21} \]

with \( K(k) \) and \( P(k) \) being the gain matrix and the covariance matrix of the estimates, respectively. The observation noise \( n(k) \) is assumed to be white with zero mean and known covariance matrix \( R(k) \). The optimal estimate is obtained by solving for the smallest error variance for the estimates. The covariance matrix \( Q(k) \) prevents the gain matrix from tending to zero. The size of the gain at which the algorithm settles, will be a compromise between tracking ability and noise sensitivity. In this sense, both the matrices \( R(k) \) and \( Q(k) \) are the design parameters of the recursive equations.

Remark 1. The solution \( \hat{\theta} \) converges to the true values \( \theta \) if the regressor vector \( \phi(k) \) and the observation noise \( v(k) \) are not correlated. In case of correlation, the estimates are biased. For example, if disturbances are not decoupled in the parity equations, the control commands in the regressor vector may be correlated with the residuals.

Remark 2. Besides the choice of \( R(k) \) and \( Q(k) \), the convergence speed depends on the excitation of the regressor vector. For example, if a failure occurs during a manoeuvre, the residuals and control commands will be much larger, than if a failure occurs during an equilibrium flight under low turbulence conditions.

Failure classification by fuzzy sets

One approach of flight control reconfiguration is Multiple Model Adaptive Control (MMAC). In MMAC, each failure hypothesis corresponds to one model and one control mode. The model and control mode that has the highest likelihood is selected. However, the likelihood test is computationally intensive because not only each component must be hypothesized but the type and magnitude must be modeled as well. Therefore, a new approach has been introduced that generalizes the MMAC approach. For several failure types a control mode is derived beforehand. However, through the use of fuzzy measures that indicate the failure states, a gradual interpolation between the control modes is achieved in contrast to the MMAC approach. Also, a smooth transition from the normal control mode to a failure mode is achieved.

For the fuzzy logic reconfiguration approach, failure classes with "soft boundaries" have to be defined. An example, consider the scaling factor of the failure model for an arbitrary actuator. Based on an estimate \( \hat{\eta} \), the failure is classified in four classes, corresponding to one “normal” and three failure types:

- \( \hat{\eta} \approx 1.0 \): the actuator is functioning normally;
- \( \hat{\eta} \approx 0.5 \): the actuator is partially degraded;
- \( \hat{\eta} \approx 0.0 \): the actuator is not functioning;
- \( \hat{\eta} \approx -1 \): the actuator is moving in the wrong direction, a sign change.

Each failure type corresponds to a particular reconfiguration strategy. A natural way of describing the failure classes is by fuzzy sets, i.e., failure classes with "soft" boundaries. In Figure 2, four membership functions are shown corresponding to the
above classes. The classes that are labelled by the linguistic terms sign change, zero, partial represent the failure types, while the normal class refers to a normal operating actuator. Depending on the estimate \( \hat{y} \), the membership degrees of the fuzzy classes indicate the failure status of the actuator. In order to avoid unnecessarily small control mode changes, the membership function are defined flat around 0.0, 0.5 and 1.0. Between the classes, the fuzzy failure classification gives a meaningful representation of various failure states. Figure 2 shows two classes for a bias failure as well. The choice of exact shape of the membership functions depends on the reconfiguration strategy and is a topic for further investigation\(^{30,31}\).

![Membership functions representing the four (failure) classes of actuator performance; sign change, zero output, partial degradation, and normal operation.]

**Figure 2:** Membership functions representing the four (failure) classes of actuator performance; sign change, zero output, partial degradation, and normal operation.

### 4. Simulation example

**Aircraft model**

The simulations are conducted on a nonlinear, six degrees of freedom model of a large transport aircraft in a landing configuration (flaps extended) under realistic assumptions about actuator dynamics, measurement noise and turbulence\(^\text{17}\). Depending on the cargo of the aircraft, the mass of the aircraft varies between 100,000 kg and 150,000 kg. The five actuators of the aircraft model are the ailerons, tailplane, rudder, and two engines. The whole tailplane functions as the pitch control. The 11 given measurements are pitch rate, roll rate, yaw rate, roll angle, sideslip angle, forward load factor, vertical load factor, airspeed, and velocities of the aircraft body in the inertial reference frame.

The aircraft is simulated in a closed-loop configuration, with longitudinal and lateral fuzzy controllers\(^\text{29}\). Additionally, turbulence and measurement noise are added. Moderate turbulence is modeled by Dryden spectra, with \( \sigma = 1.5 \) m/s. The measurement noise is modeled as zero-mean Gaussian noise with \( \sigma = 0.01 \) rad/s for angular rates, \( \sigma = 0.01 \) rad for roll and sideslip angles, \( \sigma = 0.03 \) g for accelerations, and \( \sigma = 0.1 \) m/s for the velocity measurements.

**Derivation of the parity equations**

The nominal flight conditions of the aircraft are airspeed \( V_a = 70 \) m/s, mass = 120,000 kg, and an altitude of \( h = 1000 \) m. For these conditions, the aircraft model is linearized and discretized with a sampling interval of 0.1 second, yielding a model in the form of equation (1). Then, for each of the five actuators, a parity equation is derived. The dimension of the parity equations is nine. In this way, a time period of one second serves as the time window for the parity equations.

**Remark.** Full decoupling from disturbances appeared to be not possible for all actuators. For example, a disturbance acting in the direction of the engine may not be distinguished from a change in thrust.

**The recursive equations**

For the given turbulence and measurement conditions, the 1 × 1 covariance “matrices” \( R \) are tuned for each actuator, ranging from \((0.01)^2\) to \((0.03)^2\). The remaining 2 × 2 covariance matrices \( Q \) determine the convergence speed of the scaling and bias factor estimates. Tuning of these values is done such that the convergence of the scaling factors is a little bit higher with respect to the convergence rate of the bias factor. This corresponds with the most likely appearance of the failures.

In Figure 3, the estimated values are shown under the nominal flight conditions. The estimated scaling factors are one, and the estimated bias is zero degrees, as expected. The small variation of the estimates reflects the pseudo-noise that is injected in the recursive equations.

**Remark.** Since the turbulence is not fully decoupled, and a window of measurements is used in the parity equations, the observation noise \( n(\ell) \) is zero-mean but correlated over time. This can result in small errors of the estimated scaling factors. In Figure 3, the scaling factor of rudder has a small bias error. Including a noise model in the recursive equations could in principle solve this problem.

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Nonlinear parity equations

Due to the fact that the parity equations are derived from a linear aircraft model, changing flight conditions will probably result in wrong estimates. In Figure 4, the estimates are shown for the flight conditions $V_a = 85$ m/s and mass = 110,000 kg. Due to the increased aerodynamic pressure and the lower mass, the effectiveness of the control surfaces is higher than under the nominal flight conditions. This results in “wrong” scaling factor estimates.

For this particular transport aircraft model, Takagi-Sugeno models (one for each actuator) are defined with airspeed and mass as antecedent vari-
ables. Five membership functions are defined for airspeed between 54-90 m/s, and three membership functions are defined for mass between 100,000-150,000 kg, respectively. The combinations of airspeed and mass describe 15 flight conditions which span the operating range we are interested in. The membership functions are depicted in Figure 5.

For each of the 15 flight condition, parity equations are derived. In Section 2, it was shown that using the TS model, one parity equation is obtained, in which the gains are scheduled. For illustration, one coefficient of the parity equation is shown in Figure 6 as a function of airspeed and mass. Due to the bell-shaped membership functions, a gradual, smooth interpolation is obtained.

Figure 3: Estimates for nominal flight conditions ($V_a = 70$ m/s, mass = 120,000 kg), no failure. (AL = ailerons, TA = tailplane, RU = rudder, EN1 = engine no. 1, EN2 = engine no. 2)

Figure 4: Estimates using unscheduled parity equations ($V_a = 85$ m/s, mass = 110,000 kg), no failure.

Figure 5: Membership functions for mass and airspeed.

Figure 6: One coefficient of the parity equation as a function of airspeed and mass. The stars (*) indicate the calculated values for the 15 flight conditions.

The ultimate goal of the TS models was to generate robust residuals under different flight conditions.
In Figure 7, the estimated scaling and bias factors are shown for $V_a = 85$ m/s and mass = 110,000 kg. Although small errors are observed, due to the correlated observation noise, the estimates are as desired.

Figure 7: Estimates using scheduled parity equations ($V_a = 85$ m/s, mass = 110,000 kg), no failure.

Results for three failure scenarios

The failure detection and identification system is tested by three failure scenarios:

A. An increasing bias error of the tailplane control surface from 0 to 7 degrees (0.1 degree/s).

B. Simultaneous failure of engine no. 1 and a 50% degradation of aileron effectiveness.

C. A reversal in rudder actuation.

Although the detection and identification time should be as small as possible, the first and second failure scenarios are not time-critical because the controller compensates for the failures. The third failure, however, is very time-critical because the closed-loop aircraft becomes unstable. All failures are injected at $t = 10$ seconds.

A. Tailplane bias error

In Figure 8, the estimated scaling and bias factors are shown. The flight conditions are $V_a = 58$ m/s, mass = 135,000 kg. The tailplane bias error of 0.1 degree/s is injected between $t = 10$ and 80 seconds. The pitch attitude controller automatically compensates for the bias error such that no performance degradation in terms of airspeed and altitude is observed. Figure 8 shows that the bias error is correctly estimated with a time delay of about 10-20 seconds. The time delay is rather large because the aircraft is flying in turbulence and the control excitation is small. In general, if test signals are injected, failures are identified in a much shorter time. However, test signals also may lead to passenger discomfort, system wear, or even more dangerous situations.

Figure 8: Estimates in case of 0.1 degree/s tailplane bias ($V_a = 58$ m/s, mass = 135,000 kg, failure time = 10-80 s).

In Figure 9, the membership degrees of the fuzzy classes are depicted. The membership functions that define the classes were shown in Figure 2. The results show that all scaling estimates are classified into the normal class, indicating no scaling failure. On the other hand, the membership degree for the bias class of the tailplane, converges to one, indicating a serious bias failure (dashed line). This information can be used to reconfigure the control system smoothly by direct compensating for the bias failure.

B. Engine no. 1 failure and 50% degradation of ailerons

The next scenario includes a simultaneous engine failure and 50% degradation of the ailerons. The estimated scaling and bias factors are shown in Figure 10. The flight conditions are $V_a = 85$ m/s, mass = 110,000 kg. The results show that both the scaling factors of the ailerons and engine no. 1 are correctly estimated. The bias estimates also show a bias error for engine no. 1. The estimated value corresponds exactly to the negative of the trimmed throttle position.
Figure 9: Membership degrees of fuzzy failure classes in case of increasing tailplane bias.

Figure 11: Membership degrees of fuzzy failure classes in case of engine no 1 failure and 50% degradation of ailerons.

Scaling and bias factors are shown. The flight conditions are $V_e = 58$ m/s, mass = 135,000 kg, close to stall conditions (angle-of-attack = 15 degrees). The results show that the estimated scaling factor of the rudder converges within eight seconds.

Figure 10: Estimates in case of engine no. 1 failure and 50% degradation of ailerons ($V_e = 85$ m/s, mass = 110,000 kg, failure time = 10 s).

In Figure 11, the membership degrees of the fuzzy classes are shown. First of all, the degradation of the ailerons is classified into the partial failure class. Then, the dysfunctioning of the engine no. 1 is classified into the zero operation class (dashed line), via the partial class (dash-dot line). This corresponds with the curve of the estimated scaling factor in Figure 10. The loss of the trimmed thrust is simultaneously interpreted as a bias failure.

**C. Rudder actuation reversal**

Finally, an unexpected rudder actuation reversal is simulated. The aircraft is flying under turbulent conditions, and the improper rudder deflection destabilizes the aircraft. In Figure 12, the estimated scaling and bias factors are shown. The flight conditions are $V_e = 58$ m/s, mass = 135,000 kg, close to stall conditions (angle-of-attack = 15 degrees). The results show that the estimated scaling factor of the rudder converges within eight seconds.

Figure 12: Estimates in case of rudder actuation reversal ($V_e = 58$ m/s, mass = 135,000 kg, failure time = 10 s).

The membership degrees of the failure classes are shown in Figure 13. The failure is classified into the sign change class within eight seconds after failure (dotted line). At that time, the roll angle of the aircraft is -5 degrees, the airspeed is 58 m/s, and the sideslip angle is 6 degrees, leaving enough time, in principle, to reconfigure the aircraft.
5. Conclusions

A fuzzy logic - parity space approach for the failure detection and identification problems of actuator failures of aircraft has been presented. The scheduling methodology, in the form of a Takagi-Sugeno fuzzy model, provides a convenient tool to extend linear parity equations to the nonlinear case. Local observers are selected by rules, in which the antecedent part describes the flight conditions as fuzzy propositions. Smooth or piecewise-linear interpolation between the flight conditions can be achieved by the choice of membership functions. This scheduling approach can be used for closed-loop detection filters as well.

Because the magnitude of the parity equation residuals is directly correlated to the magnitude of the failures, both scaling and bias errors can be identified using a recursive minimum-variance estimation procedure. The inclusion of pseudo-noise in the estimator dynamics keeps the identification process alert during the flight. However, due to the disturbances that are not decoupled and the fact that the residual is a moving average over a time-window, the noise in the residuals is time-correlated. Inclusion of a suitable noise model is suggested to prevent small estimation errors.

For the purpose of reconfiguration, the failures are classified with soft boundaries. Each class corresponds to a different control mode that is derived for that failure situation. Using the fuzzy classes, a gradual interpolation between different failure magnitudes is obtained and a smooth transition from the normal control mode to a failure mode can be achieved. Future work will be directed to include the failure information into fuzzy logic controllers with failure modes.

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References


Lauda Air Flight NG004 accident, Boeing 767-329ER. Phu Khao Kao Chan (Thailand), May 26, 1991.


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Feedback comments for the design in busplane and no degradation is observed in performance.