Nonlinear Rule-Based Detection and Identification of Control System Failures

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Abstract
Well-established linear procedures for detection and identification of control system failures are extended to nonlinear systems within a fuzzy logic framework. This rule-based approach has particular advantages for application to nonlinear systems that can be represented as linear parameter varying (LPV) systems. The effectiveness of the technique in the presence of modeling uncertainties, actuator dynamic failures and failures in redundant actuators is evaluated. It is pointed out that for certain practical failures, identification of the exact failure is a limitation that existing approaches to failure detection and identification do not address. Use of additional sources of information and a knowledge-based diagnostics is highlighted. Simulations conducted on a nonlinear aircraft model are included.

1 Introduction
Timely detection and identification of failures is critical to the safety of controlled systems. Among many possible failures, sensor and actuator failures have a direct impact on the performance of the control system. Actuator and sensor failures can be detected and identified by the analytical redundancy contained in the static and dynamic relationships among the actuator commands and measured outputs. Failure detection and identification (FDI) is a well-addressed topic when the control system is represented by a linear model [4, 11]. The advantage of working with linear models is that the design process is relatively simple, and topics concerned with disturbance rejection and robustness to uncertainties have been well addressed in the literature. Recent developments suggest alternatives in the form of artificial neural networks and fuzzy systems in cases where the dynamic system is nonlinear [4, 12, 20]. However, for critical systems like aircraft, the FDI systems must have a transparent structure, i.e., not black-box systems as have been applied in most cases. Therefore, the aggregation of fuzzy models [21] and (local) linear residual generators has been proposed in [18]. In this nonlinear rule-based FDI approach, the benefits from both fields are retained.

In this paper, it is shown that the nonlinear rule-based FDI approach can be applied to the class of linear parameter varying (LPV) systems. Important practical implications of the approach are then addressed. The method from [18] is summarized in Section 2. Sensitivity with respect to uncertain, non-measured parameters is discussed in Section 3. Inclusion of actuator dynamic models and the response to actuator dynamic changes is studied in Section 4. The problem of the detection and identification of redundant actuator failures is addressed in Section 5. Simulations with a realistic nonlinear model of a transport aircraft are used as examples to illustrate the approach. Section 6 ends with conclusions.

2 Nonlinear rule-based FDI
Consider the class of nonlinear processes that can be modeled as linear state-space equations with a time-varying parameter vector \( \theta(k) \). The parameter values are generally unknown a priori but can be measured on-line. These may include physical parameters as well as endogenous parameters such as the plant output [19]. This class of nonlinear systems is described by the linear parameter varying (LPV), discrete-time state equations:

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

with \( x = x_0(\theta) + \Delta x, u = u_c(\theta) + \Delta u_c, y = y_s(\theta) + \Delta y, \) and \( d = d_0(\theta) + \Delta d \). \( x \) 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 \( w \) the \( q \times 1 \) measurement noise vector. Notice that the initial conditions vary along with the parameter \( \theta \). \( A, B, C, D, E, \) and \( F \) are matrices of appropriate dimensions. Failures of control system components are modeled by \( G(\theta)f \) and \( H(\theta)f \). While the matrices in the state equations are usually given, the modes or evolutions of \( f \) and \( d \) are considered unknown.

For a particular parameter value, the LPV system dynamics are called frozen and reflect a local linearization of the process. The design of a residual generation system based on a local linearization is well addressed [4, 14, 11]. A linear residual generation system is described by:

\[
r(k) = H_u(q)\Delta u(k) + H_y(q)\Delta y(k),
\]

with \( H_u(q) \) and \( H_y(q) \) transfer function matrices and \( q \) the backward-shift operator. Although well-established for linear systems, the problem of residual generation for nonlinear systems is a topic of active research. On the other hand, parameter varying controllers can be derived for the class of LPV systems using robust control techniques [16] or using local-linear fuzzy control [21, 23], under the condition that the parameter rate is bounded [19]. The fuzzy control approach in which local controllers are selected by if-then rules, has been used in the development of a LPV residual generating system [18].

Consider the linear residual generator that is defined for the \( i \)th operating point (eq. (2)). The conditions under which the corresponding residual vector \( r_i \) holds can be expressed as fuzzy propositions in an if-then rule, like:

\[\text{If } \theta_i(k) \text{ is } S_1 \text{ and } \theta_2(k) \text{ is } S_2 \text{ and } \ldots \]

then residual is \( r_i(k) \).
Here, \( \theta = [\theta_1, \theta_2, \ldots]^T \) contains the antecedent variables (e.g., airspeed, mass, \( \ldots \)), \( S_i \) are the antecedent fuzzy sets [21], and \( r_i \) is the local linear residual (vector). 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 could be found by identification techniques [1]. The fuzzy sets are defined by membership functions \( \mu \) on \( \Theta \) with \( \theta \in \Theta \):

\[
\mu_{S_i}(\theta) : \Theta \rightarrow [0, 1].
\]

(3)

The membership functions are labelled by linguistic expressions like \textit{low, high}, etc., corresponding to the operating conditions. In the fuzzy model, all residuals contribute to the overall output, whereby each residual is weighted by the degree-of-fulfilment (truth value) of the corresponding rule. This indicates to what extent the local residual is valid, according to the conditions under which the rule holds. In this respect, the local linear scheduling approach has a clear interpretation in contrast to global, e.g., polynomial, scheduling approaches. The degree-of-fulfilment, denoted by \( \beta(\theta) \), is determined by fuzzy set operations. The product operator is used for conjunction:

\[
\beta_i(\theta) = \mu_{S_1}(\theta) \cdot \mu_{S_2}(\theta) \cdot \ldots
\]

(4)

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

\[
r(k) = \frac{\sum_{i=1}^{m} \beta_i(\theta(k)) \cdot r_i(k)}{\sum_{i=1}^{m} \beta_i(\theta(k))}.
\]

(5)

In Figure 1, the system is schematically shown. By including local residual vectors \( r_i(k) \) of the form (2) into equation (5), a LPV residual generating system is obtained:

\[
r(k) = H_u(q, \theta(k)) \Delta u(k) + H_y(q, \theta(k)) \Delta y(k),
\]

(6)

whereby the transfer function matrices are parameter varying. For a particular parameter value, the system reflects a local linear residual generating system of the process. Notice that for the determination of the control input and system output changes, the initial conditions \( u_{\theta} (\theta) \) and \( y_{\theta} (\theta) \) have to be scheduled as well.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{nonlinear_residual_generation.png}
\caption{Nonlinear residual generation.}
\end{figure}

From the magnitude of each residual \( r(k) \), the type and the magnitude of the failure can be determined by recursive least squares (RLS) methods. For example, two parameters, \( \hat{\eta}(k) \) and \( \hat{\lambda}(k) \), are simultaneously estimated for each actuator, representing multiplicative and additive failures, respectively:

\[
u(k) = \eta(k) \cdot \Delta u(k) + \lambda(k) + u_0
\]

(7)

The final decision on the failure type is performed by fuzzy logic, although a probabilistic analysis could be applied as well. Instead of crisp (failure vs. no-failure) classes, failure classes with gradual boundaries are defined. Smooth transitions and gradual interpolation between different control modes is achieved in this way [17]. As 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:

- If \( \hat{\eta} \approx 1.0 \), then actuator is functioning normally
- If \( \hat{\eta} \approx 0.5 \), then actuator is partially degraded
- If \( \hat{\eta} \approx 0.0 \), then actuator is not functioning
- If \( \hat{\eta} \approx -1.0 \), then reversal of actuation

Each failure class corresponds to a particular reconfiguration strategy. In Figure 2, four membership functions are shown corresponding to the above classes. The classes that are labelled by the linguistic terms \textit{sign change, zero, partial} represent the failure types, while the \textit{normal} class refers to a normal operating actuator. Depending on the estimate \( \hat{\eta} \), 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 for \( \eta \) are defined flat between 0.0-0.2, 0.4-0.6, and 0.8-1.0. In this way, only one or two control modes are active simultaneously when there are small fluctuations of the estimated scaling factor. Between the classes, the fuzzy failure classification gives a meaningful representation of various failure states. In Figure 2, two classes for bias failures are shown as well. In the definition of the bias membership functions, the initial (trim) conditions of the aircraft play an important role (Section 3).

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{failure_classes.png}
\caption{Failure classes.}
\end{figure}

The FDI approach has been tested on the actuators of a realistic aircraft simulation example [18]. The model is nonlinear, has six degrees of freedom, and describes a large transport aircraft in a landing configuration [13]. The five actuators of the aircraft model are the ailerons, tailplane, rudder, and two engines. The whole tailplane functions as the pitch control. The aircraft is simulated in a closed-loop configuration, and realistic assumptions on turbulence and measurement noise are included. For this particular transport aircraft model, parity equations (one for each actuator) are derived with \textit{airspeed} and \textit{mass} as antecedent variables that span the operating range of interest. From the nonlinear residual, scaling and bias terms are estimated and classified into the failure classes that are depicted in Figure 2. In the remaining part of the paper, this FDI system serves as the basis for the simulation examples.
3 Unscheduled parameters

From a practical point of view, it is not feasible to include parameters for all model uncertainties in the scheduling scheme. The FDI system would be too complex, and some uncertain parameters could not be measured on-line. With respect to these uncertain parameters, the FDI system must be made insensitive as possible.

As an example, consider variations of the center-of-mass (c.m.) of the aircraft. The position of the c.m. varies in both the longitudinal as well as the vertical direction. The estimation results of applying the FDI design to an aircraft model with an extreme c.m. position are depicted in Figure 3. Because the c.m. change affects the pitching motion, the tailplane effectiveness is slightly decreased and the tailplane bias estimate is non-zero. These "wrong" estimates can be explained by the fact that the dynamics are only slightly different from the nominal model while the trim value of the tailplane differs exactly by the estimated bias term. In other words, the c.m. variation affects only the trim values significantly, which results in correct but nonzero bias estimates.

![Figure 3: Parameter estimates in case of c.m. variation (mass = 120,000 kg, airspeed = 70 m/s).](image)

In [6, 14], methodologies have been proposed to make linear parity equations more robust against model uncertainties by (approximate) decoupling. However, decoupling cannot be applied because the uncertain trim values have a similar effect as additive failures, eq. (7). A solution is to ignore small non-zero bias estimates as long as equivalent small failures have no significant impact on the aircraft. This is automatically performed by tuning of the bias failure membership functions (Figure 2). The nonzero bias value is ignored since the kernel of the membership function of the no-bias class ranges from -2 to +2 degrees. However, this would make the identification scheme less accurate. An alternative is to pass the bias estimate through a washout or leaky integrator, that is, a high-pass filter used in autopilots to ignore steady errors. Such an approach also requires further decision logic, as now the biases can only be captured as transients.

In conclusion, a typical aircraft model uncertainty such as the c.m. position results in significantly different trim values while the impact on the system dynamics is relatively small. This is essentially a nonlinear problem that robust linear designs can not compensate. The FDI system can be made robust by tuning of failure evaluation membership functions or a complex knowledge-based decision logic.

4 Actuator dynamic changes

The actuator dynamics can be readily incorporated in the FDI system by including actuator models, see Figure 4.

![Figure 4: Including actuator dynamic models.](image)

Although the detection and identification procedures do not essentially change, the effect of realistic actuator failures has to be reconsidered. A list of possible failure types includes [20]: (i) Actuator bias, represented by the original bias errors; (ii) damaged or stuck control surface, represented by the original scaling error; (iii) change of actuator dynamics, e.g., resulting in a reduced bandwidth; (iv) reduced actuator rate limits; and (v) reduced actuator displacement limits. Figure 5 shows the the components of the actuator dynamics.

![Figure 5: Simulated actuator dynamics.](image)

The effect of the bias errors would show up in the estimated parameters as non-zero bias estimates. However, the failure types (ii) to (v) all result in a reduced effectiveness of the corresponding actuator, indicated by the $\eta$-factors. As an example, a simulation has been performed with various actuator failure types. In the aircraft model, first-order models for all actuators are included. The time constant of the rudder is then increased from 0.3s to 3s; a rate limit of 5 degrees/s is imposed on the tailplane; the ailerons are degraded by 50%; the maximum thrust of engine no. 1 is reduced to 30% of its original value, and the time constant of engine no. 2 is increased from 1.5s to 10s. All changes are induced at $t = 10s$. The estimated bias and scaling factors are depicted in Figure 6. All failures show up as scaling and/or bias errors.

Based on the parameter estimates, the failure evaluation is depicted in Figure 7. The degraded ailerons are readily identified as in the previous simulation. The rate limit of the tailplane, however, is also identified as a 50% degraded control surface (dash-dotted line). The time constant changes have only a limited effect on the estimated scaling factors of the rudder and engine no. 2. The saturation of engine no. 1 is identified as a scaling error (dash-dotted line) and a bias error (dashed line); the bias corresponds to the difference between the thrust limit and its trimmed value.

The results can be explained by the viewpoint that the scaling factor estimate serves as a describing function of the different failure types. A describing function is a linear function that approximates the transfer characteristics of a nonlinear function [5, 7]. Consider, for example, the saturation problem in Figure 8. The gain of the quasi-linear approximation depends on the magnitude and the type of the input.
hydraulic systems, electric power supplies) is required in the form of architecture, interrelations, failure probabilities, etc. This knowledge can then be implemented in a knowledge-based diagnosis system [4, 11, 22]. Then, driven by the symptoms generated by the FDI system, a search to the most-likely failure is performed by some form of uncertainty reasoning [3, 15]. Pragmatic examples of failure diagnosis systems that are applied to aeronautical systems can be found in [2, 9, 10].

5 Redundant actuator failures

5.1 Physically redundant actuators

If two actuators have a identical or an approximately identical effect on the system dynamics, failures acting on one or both actuators cannot be distinguished only by an analytical redundancy approach. Examples of such physically redundant actuators in an aircraft are upper/lower rudders and adjacent spoilers or flaps. In these cases, the corresponding columns of $K$ and $G$ in the model equations (1) are linearly dependent. In the following, it is shown how one could deal with physically redundant actuators with the help of an upper/lower rudder example.

Consider an identical rudder deflection command for both the upper and lower rudder $\delta_{R}^{(up)} = \delta_{R}^{(lo)} = \delta_{R,0 \rightarrow}$. The estimates of the scaling factor $\eta_{R}$ and the bias factor $\lambda_{R}$ for the whole rudder are composed of two indistinguishable parameters of both the upper/lower rudder:

$$
\eta_{R} = \left( \eta_{R}^{(up)} + \eta_{R}^{(lo)} \right) / 2, \quad \lambda_{R} = \left( \lambda_{R}^{(up)} + \lambda_{R}^{(lo)} \right) / 2.
$$

This means that an estimated scaling or bias failure may be the result of just one rudder or of both rudders. The only way to deal with this problem is to add two sensors that measure directly the deflections of both the upper and lower rudder, respectively (such sensors are probably already present). With the measured deflections, the separate scaling and bias factors can be readily estimated. Summarizing, we have the following estimates:

1. $(\hat{\eta}_{R}^{(up)}, \hat{\lambda}_{R}^{(up)})$ from the upper rudder sensor
2. $(\hat{\eta}_{R}^{(lo)}, \hat{\lambda}_{R}^{(lo)})$ from the lower rudder sensor
3. $(\hat{\eta}_{R}, \hat{\lambda}_{R})$ from the FDI system

Checking the above estimates seems to be rather straightforward. However, by relying on the additional sensors, we have to consider the possibility of two sensor failures as well. This complicates the diagnosis of the failure. In the following, a step-by-step procedure is introduced.

1. Check the estimates $(\hat{\eta}_{R}^{(up)}, \hat{\lambda}_{R}^{(up)})$. If the estimates do not indicate any failure, both the upper rudder as well as the upper sensor are functioning correctly.
2. Check the estimates $(\hat{\eta}_{R}^{(lo)}, \hat{\lambda}_{R}^{(lo)})$. If the estimates do not indicate any failure, both the lower rudder as well as the lower sensor are functioning correctly.
3. If one of the checks (1) and (2) indicates a failure, check the estimates $(\hat{\eta}_{R}, \hat{\lambda}_{R})$. If this check (3) does not indicate any failures, the corresponding sensor is defective. On the other hand, if (3) indicates a failure and equation (8) is satisfied, the corresponding rudder has a problem. If (3) indicates a failure while equation (8) is not satisfied, both sensor and rudder failed.
4. If both the checks (c1) and (c2) indicate a failure, a cross-check with the estimates \( \{ \hat{a}_1, \hat{a}_2 \} \) can again be performed. If equation (8) holds, the only conclusion is that both sensors have failed. On the other hand, if both (c1) and (c2) indicate a failure but the estimates \( \{ \hat{a}_1, \hat{a}_2 \} \) are just zero and one, respectively, the only conclusion is that both sensors have failed.

5. The remaining possibility is that all estimates indicate failures while not satisfying equation (8). In this case, one or two sensors and one or two actuators have failed, including at least one sensor or actuator from both the upper and lower pairs.

Although the most likely failure hypotheses can be checked, the two sensors still do not provide a unique outcome of the failure diagnosis procedure. In order to select the most likely hypothesis from the remaining possibilities, complex knowledge-based decision logic is again required.

5.2 Functionally redundant actuators

The linear FDI approaches generally use decoupling to distinguish failures between the different control system components and to achieve insensitivity with respect to disturbances (and possibly model uncertainties). The number of independent inputs that can be decoupled is, however, limited by the order of the system. In order to deal with many disturbances and model uncertainty inputs, approximate decoupling can be applied [6]. In order to deal with many functionally redundant control surfaces and sensors like in aircraft, a bank of FDI systems has to be defined in a pragmatic way such that the isolation property is retained [8]. In the definition of such a bank, actuators (and sensors) that are most likely to fail simultaneously should be grouped (e.g., a set of control surfaces that are powered by the same hydraulic system). If one or two actuators that are grouped fail, most residuals in the other FDI banks will be non-zero and these banks could be ignored. However, an in-depth probabilistic analysis is necessary to identify the right bank.

6 Conclusions

Linear FDI systems can be readily extended by fuzzy rule-based methods to the class of LPV processes, e.g., aircraft under varying flight conditions. The nonlinear residual generator discussed in this paper provides a transparent structure that is important for validation when applied to safety-critical control systems like aircraft. Although several important properties are demonstrated, such as, robustness to varying operating conditions and disturbances, and identification of biases and scale-factors, nonlinear problems pose several practical limitations. Analytical FDI approaches are limited to a high “monitoring” level, providing failure detection information. In order to identify and isolate the exact failure source, however, a knowledge-based failure diagnosis is required. This is particularly true for various dynamic and nonlinear control system changes and failures in redundant components.

Acknowledgements

Support for G. Schram was provided by the Dutch Organization for Scientific Research (NWO) Grant No. SIR-13-4298, and support for S.M. Gospetcy and R.F. Stengel was provided by the Federal Aviation Administration (FAA) Grant No. 95-G-022.

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