Smart Reconfigurable Fault-Tolerant Flight Control Against Actuator Failures

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Abstract: In this study, active fault tolerant flight control technique with actuation reconfiguration is proposed. For this purpose two-stage Kalman filter (TSKF) is designed to identify the control distribution matrix elements corresponding to the faulty actuator, and a control reconfiguration action is taken to keep the performance of the impaired aircraft same as that of the unimpaired aircraft. Thus the control reconfiguration is carried out using identified control distribution matrix. In the simulations, the nonlinear flight dynamics of an AFTI/F-16 fighter model is considered, and actuator failure identification and reconfigurable control are examined.

Keywords: Fault tolerant systems, Fault identification, Aircraft control, Kalman filters, Estimation parameters

1. INTRODUCTION

Research into fault-tolerant control is a very actual problem and attracts many investigators. Blanke (1999) defines fault-tolerant control as “a system which is able to continue operation after a failure; a degradation of performance may be accepted”. Their proposed solutions have fallen into two categories: passive (Zhao and Jiang, 1998; Liu, 2001; Tao et al., 2001) and active (Wu et al., 2000; Zhang and Jiang, 2002; Hajiyev and Caliskan, 2003; Liu et al., 2004). In the passive category, the impaired system continues to operate with the same controller; the effectiveness of the scheme depends upon the original control law’s possessing a considerable degree of robustness.

The passive methods are essentially robust control techniques which are suitable for certain types of structural failures. These failures can be modeled as uncertainty regions around a nominal model of system. There are many types of common failures, which cannot be adequately modelled as uncertainty. Therefore, it is important to constitute the controller, which more directly addresses the concrete situation.

The active category involves either an on-line re-design of the control law after failure has occurred and has been detected, or the selection of a new pre-computed control law. In this study an active fault-tolerant control system against different degree of actuator failures is considered.

The active fault-tolerant control systems consist of two basic subsystems (Patton, 1997):

1. Fault detection and isolation (FDI) or system identification, and
2. Control reconfiguration or restructure.

In an active fault-tolerant control system, faults are detected and identified by a FDI scheme, and the controllers are reconfigured accordingly on-line in real-time. An effective FDI procedure is critical for designing high performance active fault-tolerant control systems. Many model-based FDI techniques have been developed to detect and identify sensor and actuator faults by using analytical redundancy, state estimation and parameter identification (Maybeck, 1999; Keller, 1999; Larson et al., 2002; Lee and Lyou, 2002; Hajiyev and Caliskan, 2001, 2003, 2005).

The proposed methods in (Wu et al., 2000; Zhang and Jiang, 2002; Liu et al., 2004) based on the estimation of effectiveness factor of the faulty actuator. The actuators are 100% effective (in executing the control commands), if during normal operation, the actuators operate exactly as directed by the controller. When faults occur in actuators, such as partial loss of a control surface, or pressure reduction in hydraulic lines, in the case of an aircraft, partial blockage of a control valve in process control, or voltage reduction/amplifier saturations in electrical servo systems, the actuators would not be able to fulfill the control commands completely. In such cases, it is said that the effectiveness of the actuators has been reduced (Zhang and Jiang, 2002).

In the above papers to quantify faults entering control systems through actuators, a parameter known as the reduction of the control effectiveness factor is used (Wu et al., 2000), which represents the loss of the one-to-one relationship between the control command and the true actuator actions. In these studies, the control effectiveness factor is employed as the actuator fault parameter and estimated via Kalman filter. But the control effectiveness factor of faulty actuator is assumed as the same for all elements of corresponding control distribution vector (or appropriate column of control...
distribution matrix). In practice, it can be met certain surface faults, for instance partial loss of a control surface (break off part of control surface), which causes to the different control effectiveness factors of the actuator.

In this study, the reconfiguration technique based on the two-stage Kalman Filter (TSKF), which estimates both the system state variables and the control distribution matrix elements corresponding to the faulty actuator will be introduced and discussed. Thus the control reconfiguration is carried out using identified control distribution matrix. Simulation results on an AFTI/F-16 fighter nonlinear dynamic model have demonstrated the effectiveness of the proposed method.

2. DESIGN OF TSKF FOR AIRCRAFT STATE VECTOR ESTIMATION AND ACTUATOR FAULT IDENTIFICATION

2.1. AFTI /F-16 Aircraft Model Description

The technique for actuator failure identification is applied to an unstable multi-input multi-output model of an AFTI/F-16 fighter. The fighter is stabilized by means of a linear quadratic optimal controller. The control gain brings all the eigenvalues that are outside the unit circle, inside the unit circle. It also keeps the mechanical limits on the deflections of control surfaces. The model of the fighter is as follows:

\[
x(k+1) = Ax(k) + Bu(k) + F(x(k)) + Gw(k)
\]

(1)

The aircraft state variables are:

\[
x = [v, \alpha, q, \beta, p, r, \phi, \psi, \omega]^{T},
\]

where, \(T\) is the sign of transposition, \(v\) is the forward velocity, \(\alpha\) is the angle of attack, \(q\) is the pitch rate, \(\theta\) is the pitch angle, \(\beta\) is the side-slip angle, \(p\) is the roll rate, \(r\) is the yaw rate, \(\phi\) is the roll angle, and \(\psi\) is the yaw angle, \(w(k)\) is the system noise with zero mean and the correlation matrix \(E[w(k)w^T(j)] = Q(k)\delta(kj)\).

The fighter has six control surfaces and hence six control inputs are:

\[
u = [\delta_{hr}, \delta_{hr}, \delta_{fr}, \delta_{rr}, \delta_{cr}, \delta_{sr}],
\]

where \(\delta_{hr}\) and \(\delta_{hl}\) are the deflections of the right and left horizontal stabilizers, \(\delta_{fr}\) and \(\delta_{fl}\) are the deflections of the right and left flaps, \(\delta_{cr}\) and \(\delta_{sr}\) are the canard and rudder deflections.

2.2. Deriving of TSKF for the F-16 Aircraft Model Estimation

Let us apply the Kalman filter to estimate this vector and the control distribution matrix elements corresponding to the faulty actuator. The nonlinear mathematic model for the longitudinal and lateral F-16 aircraft motion is given in (1). The measurement equations can be written as:

\[
z(k) = Hx(k) + V(k)
\]

(2)

where \(H\) is the measurement matrix, which is \(9 \times 9\) unit matrix, \(V(k)\) is the measurement noise. The statistical characteristics of the system and measurement noises are submitted as following expressions

\[
E[w(k)] = 0;
E[w^T(j)] = Q(k)\delta(kj);
E[V(k)V^T(j)] = R(k)\delta(kj).
\]

Here \(E\) is the operator of statistical averaging; and \(\delta(kj)\) is the Kronecker delta symbol. Note that \(\{w(k)\}\) and \(\{V(k)\}\) are assumed mutually uncorrelated.

Let us assume that, the actuator fault detection and isolation problem is solved. It is required to perform the actuator fault identification and control reconfiguration. In case of a fault in the \(i\)th actuator, the control distribution matrix \(B = [h_1, h_2, \ldots, h_i, \ldots, h_p]\) changes to \(B' = [h_1, h_2, \ldots, h_i', \ldots, h_p]\), where \(h_j \in R^{N_x}, j = 1, \ldots, p\), and the F-16 Aircraft state model with actuator faults can be written as:

\[
x(k+1) = Ax(k) + B'u(k) + F(x(k)) + Gw(k),
\]

(4)

where the post-fault term \(B'u(k)\) in the equation (4) relates to the fault-free term \(B'u(k) = [h_1, h_2, \ldots, h_i, \ldots, h_p]\) and the faulty term \(b'_i u(k)\) as below

\[
B'u(k) = [h_1, h_2, \ldots, h_i, \ldots, h_p]u(k) + b'_i u_i(k)
= B'u(k) + b'_i u_i(k)
\]

(5)

where \(B' = [h_1, h_2, \ldots, h_i, \ldots, h_p]\) is the fault-free control distribution matrix, \(b'_i = [b'_{i1}, b'_{i2}, \ldots, b'_i]\) is the faulty control distribution vector.

Taking into consideration (5) the F-16 Aircraft state model after actuator fault can be rewritten in the form:

\[
x(k+1) = Ax(k) + B'u(k) + b'_i u_i(k) + F(x(k)) + Gw(k),
\]

(6)

Thus the fault augmented model has the following form:

\[
x(k+1) = Ax(k) + B'u(k) + b'_i u_i(k) + F(x(k)) + Gw(k)
\]

(7)

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(7)  
\[
b'_i(k+1) = b'_i(k) + w'_i(k) \\
z(k) = H\hat{x}(k) + V(k)
\]

where the noise sequences \(w(k), w'_i(k)\) and \(V(k)\) are assumed to be zero mean uncorrelated white Gaussian noise sequences with

\[
E\left[\begin{bmatrix} w(k) \\ w'_i(k) \\ V(k) \end{bmatrix}\right] = \begin{bmatrix} Q & 0 & 0 \\ 0 & Q' & 0 \\ 0 & 0 & R \end{bmatrix} \delta(kj)  
\]

Here \(Q > 0, Q' > 0, R > 0\).

An augmented state Kalman filter (ASKF) (Friedland, 1969; Keller, 1997; Hajiyev and Caliskan, 2001) may be used to produce the optimal augmented state \(X^*(k+1) = [x(k+1), b(k+1)]\) estimate. The problem with this approach is that, the computational requirement of the ASKF may become excessive. In addition, numerical problems may arise during the implementation, mainly for ill-conditioned systems. The ASKF for solving this problem will be in dimension \(N+p\). When \(p\) is comparable to \(N\), the dimension of the new state vector \(X(k+1)\) becomes substantially large. The problem is to develop two parallel reduced-order filters, which can estimate the augmented state of system.

Based on the models given by (7) - (8), TSKF below may be used to estimate the F-16 Aircraft state variables and the control distribution matrix elements corresponding to the faulty actuator is obtained.

State estimator (the second stage of estimation)

\[
\hat{x}(k+1/k) = A\hat{x}(k/k) + \hat{B}u(k) + F(\hat{x}(k/k)) = A\hat{x}(k/k) + \hat{B}u(k) + F(\hat{x}(k/k))
\]

\[
P(k+1/k) = AP(k/k)A^T + \hat{B}D_x\hat{B}^T + F(\hat{x}(k/k))F^T + GG^T
\]

\[
\tilde{x}(k+1/k+1) = \hat{x}(k+1/k) + K(k+1)[z(k+1) - H\hat{x}(k+1/k)]
\]

\[
K(k+1) = P(k+1/k)H^T[H\hat{x}(k+1/k)H^T + R]^{-1}
\]

\[
P(k+1/k+1) = [I - K(k+1)H]P(k+1/k)
\]

where the filter innovation sequence and its covariance matrix are given as

\[
\nu(k+1) = z(k+1) - H\hat{x}(k+1/k) \\
P_e(k+1) = R + HP(k+1/k)H^T
\]

Here \(\hat{x}(k+1/k)\) is the extrapolation value of the state vector; \(\hat{x}(k+1/k+1)\) is the estimation value of the state vector; \(\nu(k+1)\) is the estimation error. It can be written from (6)

\[
b'_i u_i(k) = x(k+1) - Ax(k) - B'u(k) - F(x(k)) - Gw(k).
\]

The variable

\[
E\Omega(k+1) = z(k+1) - A\hat{x}(k/k) - B'u(k) - F(x(k)) - \zeta(k+1)
\]

may be used as the measurement value of the term \(b'_i u_i(k)\), where \(\zeta(k+1)\) is the measurement noise of \(\Omega(k+1)\), its covariance matrix is

\[
P_e(k+1) = E\{\xi(k+1)\xi^T(k+1)\} = R + AP(k/k)A^T + B'D_xB^T + F(\hat{x}(k/k))F^T + GG^T
\]

\[
F_i = \frac{\partial F(x)}{\partial x}_{|x(i)} \text{ is the Jacobian of } F(x) \text{ evaluated at } x(k) = \hat{x}(k/k).
\]

Thus faulty control distribution vector model can be presented in the following form

\[
b'_i(k+1) = b'_i(k) + w'_i(k) \\
\Omega(k+1) = b'_i(k)u_i(k+1) + \zeta(k+1)
\]

(14)

Applying Kalman filter (9) with parameters

\[
A = I, \\
H = u_i(k+1), \\
Q(k+1) = Q_e(k+1) = E\{w'_i(k+1)(w'_i(k+1))^T\}, \\
E\{\xi(k+1)\xi^T(k+1)\} = P_e(k+1)
\]

to model (14) and keeping in mind that the covariance matrix of measurement noise \(\Omega(k+1)\) is determined by expression (13), we obtain the following algorithm for estimation of the faulty control distribution vector...
\[ \dot{\hat{y}}(k+1/k) = \dot{\hat{y}}(k/k) \]
\[ P_{\hat{y}}(k + 1/k) = P_{\hat{y}}(k/k) + Q(k) \]
\[ \dot{\hat{y}}(k+1/k+1) = \dot{\hat{y}}(k+1/k) + K^+(k+1) \times \left( \Omega(k+1) - \dot{\hat{y}}(k+1/k)u(k+1) \right) \]
\[ K^+(k+1) = u_c(k+1)P_{\hat{y}}(k/k+1) \times \left[ P_{\hat{y}}(k+1/k+1)+u_c^2(k+1)P_{\hat{y}}(k/k+1)+\dot{\hat{y}}(k/k+1)D_{\hat{y}}(\dot{\hat{y}}(k/k+1))^T \right]^{-1} \]
\[ P_{\hat{y}}(k+1/k+1) = \left[ I - u_c(k+1)K^+(k+1) \right]P_{\hat{y}}(k+1/k) \]  
(15)

where \( \dot{\hat{y}}(k+1/k) \) is the extrapolation value; \( P_{\hat{y}}(k+1/k) \) is the covariance matrix of extrapolation errors; \( K^+(k+1) \) is the gain matrix of the Kalman filter.

The set of equations (9) and (15) represent a two-stage Kalman filter procedure and makes it possible to estimate both the aircraft state variables and the control distribution matrix elements which correspond to the faulty actuator. In the proposed TSKF algorithm, the faulty control distribution vector estimator (set of equations (15)) is the first stage of estimation and state estimator (set of equations (9)) is the second stage of estimation. As it is seen from expressions (9) and (15), the parameters of one of the filter are automatically adapted to the variations of the other filter.

3. TSKF BASED RECONFIGURABLE CONTROL FOR THE ACTUATOR FAILURES

As a result of performed two-stage Kalman filter procedure, the estimates of the state vector \( \hat{x} \) and the control distribution matrix elements corresponding to the faulty actuator \( \dot{\hat{y}}(k) \), are obtained. Then a new (reconfigured) control distribution matrix \( \hat{B} = [b_1, b_2, ..., \dot{\hat{y}}(k), ..., b_p] \) is composed. Since the aircraft is unstable, it is stabilized by the stochastic control technique based on the proposed TSKF (9)-(15). Linear quadratic regulator is adopted in this study as a optimal control technique. The performance index to be minimized is as follows:

\[ J = \sum_{i=1}^{k} \left[ \hat{x}^T(i)Q\hat{x}(i) + u^T(i)R_u(i) \right] \]

where \( Q \) is a semi-positive definite symmetric matrix and \( R_u \) is a positive definite symmetric matrix. The control input is computed as:

\[ u(k) = -K_u(k)\hat{x}(k) \]

where

\[ K_u(k) = \left( R_u + \hat{B}^T P_e(k) \hat{B} \right)^{-1} \hat{B}^T P_e(k)A \]  
(18)

and the matrix \( P_e(k) \) is found iteratively backwards in time by the dynamic Riccati equation:

\[ P_e(k-1) = Q + A^T \times \left[ P_e(k) - P_e(k)\hat{B}\left( R_u + \hat{B}^T P_e(k)\hat{B} \right)^{-1} \hat{B}^T P_e(k) \right] A \]

As it is seen from equations (17)-(19), the control reconfiguration procedure is executed by considering the identified (reconfigured) control distribution matrix. A structure for the active fault tolerant aircraft flight control system with reconfiguration against actuator failures is presented in Figure 1.

4. SIMULATION RESULTS

The technique for active fault tolerant control with reconfiguration against actuator failures is applied to multi-input multi-output model of an AFTI/F-16 fighter (1). The model parameters \( A, B, \) and \( F(x(k)) \) are calculated for the sampling period of 0.03 s.

The measurements were processed using TSKF (9)-(15) that allows to determine the estimates of the state vector of F-16 aircraft and the control distribution matrix elements corresponding to the faulty actuator at each \( k \) step. In simulations the first control surface (right horizontal stabilizer) has been changed at iteration 230.

The control law is found according to the LQR optimal control approach as explained in section 3. Two simulation results are presented below. In the first simulation, we continue to use the old optimal control law after the actuator failure. In the second one, we re-compute the optimal control law after the actuator failure has occurred since we have already detected and identified the failure and thus we know the failure time and failure type. In this case the control reconfiguration procedure is executed by considering the identified control distribution matrix. The new control input is found by computing the gain matrix for the actuator fault, identified via two-stage Kalman filter algorithm.

A part of simulation results are presented in Figures 2-5. Figures 2,3 show the pitch rate and pitch angle of aircraft with the old control law, and Figures 4,5 - reconfigured control law. The obtained results show that the control reconfiguration is realized for the impaired aircraft control system. The graphs given in Figures 2,3 show that, the surface fault has caused impaired aircraft dynamics. The graphs given in Figures 4,5 show that the reconfigurable controlled aircraft dynamics converges to the unimpaired aircraft dynamics. Similar results are obtained for the rest of the state variables of aircraft.

5. CONCLUSION

An active fault tolerant control technique with reconfiguration against actuator failures is presented. An actuator fault detection algorithm based on the two-stage
Kalman filter is proposed and a control reconfiguration action is taken to keep the performance of the impaired aircraft same as that of the unimpaired aircraft. TSKF is designed to estimate the system state variables and to identify the control distribution matrix elements corresponding to the faulty actuator, and thus the control reconfiguration is carried out using identified control distribution matrix.

The actuator fault identification problem is solved through two jointly operating Kalman filters: The first one is for the estimation of the control distribution matrix elements corresponding to the faulty actuator and the second one is for the estimation of the state variables of an aircraft model. The parameters of one of the filter are automatically adapted to the variations of the other filter.

The theoretic results are confirmed by the simulation results carried out on a model of the nonlinear flight dynamics of an AFTI/F-16 fighter. The simulation results show that the reconfigurable controlled aircraft dynamics converges to the unimpaired aircraft dynamics.

REFERENCES


Fig. 2. Pitch rate for unimpaired (solid line) and impaired (dashed line) aircraft without reconfiguration, and the error between them.

Fig. 3. Pitch angle for unimpaired (solid line) and impaired (dashed line) aircraft without reconfiguration, and the error between them.

Fig. 4. Pitch rate for unimpaired (solid line) and impaired (dashed line) aircraft with reconfiguration, and the error between them.

Fig. 5. Pitch angle for unimpaired (solid line) and impaired (dashed line) aircraft with reconfiguration, and the error between them.