Failure Detection of Aircraft Engine Output Sensors via Bayesian Hypothesis Testing

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Introduction

THE last two decades have been significant for advancements in control systems. The development of state space analyses has made possible the application of modern control techniques to real problems. The potential for applied modern control theory in the design of future generations of aircraft engines has been recognized by contemporary researchers.[1,2] The use of multiple hypothesis testing techniques for detecting the failure state of rate sensors on modern aircraft has been noted.[3] Extension of these ideas to the aircraft engine problem was first considered by De Silva.[4] Further extensions to the problem of large variations in the system output are treated in the present paper.

Assumptions and Equations

In considering the engine as a multi-input/multi-output system, fuel flow and altitude are considered as the control variables. The state vector normally includes engine rotor speed, compressor discharge temperature, compressor discharge pressure, nozzle inlet temperature, nozzle inlet pressure, turbine inlet temperature, turbine inlet pressure, and engine thrust.

Of the various state components that are of interest in the control of turbojet engines, the rotor speed, temperatures, and pressures can be directly measured. The engine thrust has to be computed using the mass flow and aircraft speed data.[5,6]

Different ranges of temperatures are of interest in turbojet engine control. For example, the inlet temperature may vary from −100°F to 600°F and the turbine temperature can be anywhere between 400°F and 2500°F. One important consideration here is whether it is static temperature or the total temperature that one wishes to measure. A thermocouple in an incompressible fluid measures the total temperature. It has a fast response but a low sensitivity and is particularly suitable for moderately high temperature measurements. Solid, liquid, or gas expansion thermometers are suitable for low temperatures. Semiconductor devices such as thermistors are highly sensitive because their resistance decreases with increasing temperature. X-ray absorption units and radiation pyrometers may be used for very high temperature.

Inlet pressure can be from 3 psi to 50 psi and burner pressures in the range of 30 psi to 1500 psi are possible. Here, too, one has to distinctly identify the total pressure from static pressure. Piezo-electric devices can be used for very accurate pressure measurements. Pitot tubes, bourdon tubes, and manometers are also commonly used. There are also diaphragm devices which measure the pressure.

Principal volume flow measuring devices include positive displacement flow meters, velocity meters, orifice meters, and venturi meters. In variable-area rotometers a restriction is supported by fluid flow inside a tapered tube mounted vertically. Flow will move the restriction until the pressure drop through the annular area between the restriction and the tube balances the weight of the restriction.

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Mass flow can either be computed, using the volume flow rate and density information, or directly measured, using mass flow meters. Magnus effect meters use the principle that when a rotating cylinder intercepts the mass flow, a pressure difference is created between the advancing and receding surfaces. Impact flow meters and acceleration mass flow meters are also common.

The flight speed is normally determined by first obtaining the static and total pressures on the aircraft surface using a pitot-tube device. The velocity of the aircraft relative to air can then be evaluated. The results can in turn be reduced to the ground speed using information regarding the atmospheric air.

The turbojet engine can be modeled in terms of a set of first-order nonlinear ordinary differential equations

$$\dot{z}=f(z,p) \tag{1}$$

$$\xi=\xi(z) \tag{2}$$

where z is the state vector, p is the input vector, and ξ is the output measurement vector.

If the state, control, and measurement vectors are linearized about their steady state values z_s, p_s, and ξ_s, respectively, we obtain

$$\dot{x}=Ax+Bu \tag{3}$$

$$y=Cx \tag{4}$$

where

$$x=z-z_s$$

$$u=p-p_s$$

$$y=\xi-\xi_s$$

and

$$A=\partial f/\partial z(z_s,p_s)$$

$$B=\partial f/\partial p(z_s,p_s)$$

$$C=\partial \xi/\partial z(z_s)$$

Hypothesis Testing

The problem is that of making a decision which is best depending on past observations from a stochastic environment. Suppose the system can assume M disjoint states $H_1, H_2, \ldots, H_M$ with a priori probabilities $P_{H_1}, \ldots, P_{H_M}$, respectively. H_i are known as the hypotheses. The hypothesis testing decision problem now becomes picking the most likely hypothesis depending on the observations y and based upon a suitable test. For the purposes of this analysis, the Bayes test was selected.

In the Bayesian approach, the risk function is the expected value of the cost of making an incorrect decision. This can be expressed as

$$\mathcal{B}=\sum_{i=1}^{M}\sum_{j=1}^{M}C_{ij}P(H_i,H_j) \tag{5}$$

where $P(H_i, H_j)$ is the joint probability that H_i is accepted and H_j is true.

The multiple hypothesis testing involves the partitioning of the entire observation space Z into M disjoint subspaces Z_i $(i=1, 2, \ldots M)$. The subspaces Z_i are determined by minimizing the risk function $\mathcal{B}$. This result is further written as

$$\mathcal{B}=\sum_{j=1}^{M}C_{jj}P_{H_j}+\sum_{i=1}^{M}\int_{Z_i}\left(\sum_{j=1}^{M}\beta_{ij}\right)\mathrm{d}y \tag{6}$$

where

$$\beta_{ij} = (C_{ij} - C_{jj}) P_{H_j} \underset{Y/H}{f(y/H_j)} \quad (7)$$

P_{H_j} is the a priori probability of occurrence of H_j

$\underset{Y/H}{f(y/H_j)}$ is the conditional probability density of the observation random vector given that H_j is true

Note that $\beta_{ii} = 0$ for all i, $\beta_{ij} > 0$ for $i \neq j$, and $C_{ij} < C_{ii}$ for any i and for all $j \neq i$. Then, for a particular observation sample y, if the minimum of

$$\sum_{\substack{j=1 \\ j \neq i}}^{M} \beta_{ij}$$

corresponds to $i = l$ we accept the hypothesis H_l.

In the case of Gaussian statistics for the initial states and measurement vectors, the conditional probability density of the observation vector is

$$\underset{Y/H}{f(y/H_i)} = \frac{\exp[-\frac{1}{2}(y-\hat{y}_i)^T V_i^{-1}(y-\hat{y})]}{(2\pi)^{m/2} |V_i|} \quad (8)$$

where $\hat{y}_i$ is the expected value of the measurement vector conditioned on hypothesis H_i, and V_i is the covariance matrix of the hypothesis-conditioned measurement error $y - \hat{y}_i$.

Under these conditions, the testing algorithm is simply:

$$\text{accept } H_l \text{ if } \alpha_l \leq \alpha_i \text{ for all } i \neq l$$

where

$$\alpha_i = \ell n |V_i| + \frac{1}{2}(y-\hat{y}_i)^T V_i^{-1}(y-\hat{y}_i)$$

The decision logic assumes the availability of the measurement error samples $y - y_i$ and corresponding covariance matrices V_i conditioned on each hypothesis H_i at each sampling instant. This then allows a decision to be made in every sampling instant. The hypothesis-conditioned errors and the covariance matrices may be obtained from a bank of M Kalman filters.

Numerical Example

The effectiveness of the test is demonstrated for a second-order linear state model developed by Merrill. The engine rotational speed and engine thrust are chosen as the state variables and the input control variable is the fuel flow. Since large variations are allowed in the output variables, several operating nominals in engine speed are used for linearization purposes, ranging from 36,221 rev/min to 37,116 rev/min.

Three possible failure states are considered: H_1 – speed sensor failed; H_2 – thrust sensor failed; and H_3 – no sensor failure.

A measurement noise covariance matrix has to be assumed under each failure state H_i with a corresponding higher value associated with a failed sensor. The following failure modes were simulated:

1) During 0.0-5.0 s there was no sensor failure.
2) During 5.1-10.0 s the speed sensor failed.
3) During 10.1-15.0 s the thrust sensor failed.
4) During 15.1-20.0 s there was no sensor failure.
5) During 20.1-30.0 s the speed sensor failed.
6) During 30.1-40.0 s there was no sensor failure.

An indicator function I was defined as follows:

$$I = 0.0 \text{ when } H_1 \text{ is true}$$
$$= 0.5 \text{ when } H_2 \text{ is true}$$
$$= 1.0 \text{ when } H_3 \text{ is true}$$

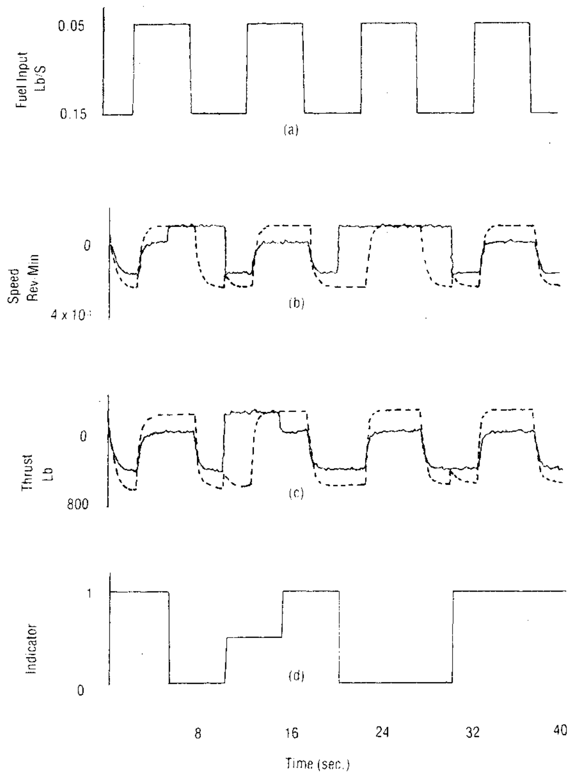

Fig. 1 Speed and thrust sensor failure detection.

Figure 1 gives the results of applying the decision technique to the engine model for a bang-bang input. The curve (a) represents the fuel flow input. Curves (b) and (c) are the readings of rotor speed sensor and thrust sensor, respectively. Curve (d) gives the indicator function as determined by the decision logic. It is seen that in all cases the decision logic has determined the failure states exactly. The broken curves give the optimal estimates of the rotor speed and thrust respectively. These estimated outputs can be used to control the engine in the event of a sensor failure.

Conclusions

A technique that uses Bayesian hypothesis testing and a set of hypothesis-conditioned Kalman filters to detect the failure states of aircraft engine sensors and to estimate the outputs corresponding to the failed sensors has been presented. The technique was applied to a single-spool turbojet engine model experiencing large variations in the output variables. In this case the decision logic detected the sensor failures exactly. A desirable feature of the technique is that optimal estimates of the outputs corresponding to failed sensors are a by-product of the decision process. However, the technique requires as many Kalman filters as there are failure states.

References

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