STRUCTURE AND METHOD OF THE EXPERT SYSTEM FOR SENSOR FAILURE DETECTION OF AIRCRAFT

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Abstract

In this paper, an expert system for the sensor failure detection and isolation of flight test system is introduced. In order to detect and locate faults of an aircraft's sensors with sufficient robustness to parameter changes and noise, accurate discrete-time models is presented and multi-level separated-bias algorithm is used for residual sequence generation. The expert system is used for the difficult task of failure isolation and flight decision making. Structure and mehtod for building the expert system is introduced. The results of simulation and actual application show that the expert system for the FDI (failure detection and isolation) of flight test instruments can declare the faulty and locate the failures correctly. This expert system is suitable not only to the flight regime of low angle of attack but also to the flight regime of high angle of attack.

I. Introduction

A wide variety of techniques has been proposed in recent years for the detection and isolation of failures in aircraft engine output sensors and airborne flight test systems (de Silva,1982; Patton, 1986). In one way or another, all these methods involve the generation of signals that are accentuated by the presence of particular failures if these failures have actually occurred. Looking into the literature on FDI based on analytical redundancy one can see that the wide variety of methods can raughly be devided into two major groups: (i) parameter estimation method, (ii) state estimation methods. The parameter estimation approach employs on-line identification of the mathematical model in order to determine the physical coefficients of the process, the state estimation approach restricts to the on-line reconstruction of sets or subsets of state or mesured variables taking the mathematical model to be given. This is done with the aid of observer or extended Kalman filters whose estimates or innovations are then used for residual deneration. In practice, There are two weak points in the parameter estimation approach. First, what is really identifiedare not the physical coefficients of the process but the parameters of its mathematical model. These actually depend on the choise of the model and there is in general no unique relationship backward from the mathematical parameters to the physical coefficients. Second, though well apt for simple cases, the standard parameter estimation method fail when the process contains nonlinearities. Most of the FDI methods have therefore adopted the state estimation approach. Since biases and unknown scale factors are usually presented in flight test data, these instrumentation errors must also be estimated. In order to solve this problem, the biases and scale factors are usually considered as componets of a so-called augmented state vector. Then extended Kalman filter is used for both the state and biases estimation. This approach, However, may be unable to declare the faulty and locate the failures correctly because big modelling errors may often appear when aircraft maneuvers especially when high angle-of-attack maneuvers and because it is too difficult for the ordinary approach to achive on-line state estimation (Shi, 1989; Wang, 1988). On the other hand, failure isolation and flight decision are also very difficult taskes. For these reasons an accurate discrete-time model and robust residual generation method are presented and an expert system for the FDI of flight test system is introduced.

II. Basic Structure of Expert System

The goal of FDI is to detect and locate failures of the sensors of flight test instruments with sufficient robustness to system parameter changes and noises. Sensor faulty must be distinguished from ' wild ' data firstly. Otherwise, what is really detected may not be the sensor failures of flight test system but the effection of the ' wild ' data. Another important things is to distinguish output sensor faulty from computed output faulty to get high efficiency of failure isolation. Thus, the basic idea of the design of the expert system for FDI is given as follows. First, the residuals are compared with predetermined thresholds. If the residuals of certain sensors remain below the thresholds the corresponding sensors are declared unfaulty; if the residual surpasses the threshold the expert system will first distinguish the fault from the effects of ' wild ' data. If fault occurs, the inference engine will carry out what kind of the fault may be, the measured output or computed output? If the measured output is fault the corresponding instrument is declared faulty and an alarm is released. If the computed output is fault sensitivity to process parameters or state variations is calculated and the results are given to the expert system. The expert system may accomplish the dificult tasks of failure isolation and flight decision making. In order to detect the failures of the instruments in various flight test the thresholds may actually be made adaptive to the flight maneuver shapes and to the flight regimes of both low and high angle of attack. Thus the expert system, ES can be structured.

Data base: The data base of the expert system should include the aeroynamic models of aircraft to be tested, the experiential threshold values, the inputs of elevator deflection, aileron deflection, rudder deflection, and other control signals, flight parameters. These data may be used to (1) distinguish sensor failure from ' wild ' data; (2) distinguish the fault of measured outputs and computed outputs. Knowledge base and inference engine may directly use any of the experimental data in the data base.

Knowledge base: The function of the knowledge base is to provide knowledge sources to the inference engine of expert system.

In general the fault may be one of the following three cases:

(1) Measured output is correct, computed output is fault;

(2) Measured output is fault, computed output is correct;

(3) Both measured output and computed output are all fault.

The knowledge base can provide the knowledge source of distinction between ' wild ' data and failures and the knowledge source of distinction of measured output error from computed output error.

Since the threshold logic is a most simple and common decision strategy, the thresholds should acctually be changed in different flight test and flight maneuvers. In the knowledge base the thresholds may be made adaptive to the flight maneuvers and to the angle of attack on the basis of the knowledge source of the experiences of many many knowledge engineers.

The knowledge base may have the explanation functions. When fault occurs, the inference engine will indicate the failures of certain sensors and the commander or aviator can ask ' why the conclusion is carried out ' and other questions.

The knowledge base is also of the function of knowledge acquisition. For more experienced users, the engineer will be allowed to enter the facts into the knowledge base. In oder to make decision for flight, the knowledge source and commander's idea will directly be given to inference engine.

The nodes of the knowledge base are the posibilities of the sensor failures of three position angles θ, ϕ, and ψ; three linear accelerations A_x, A_y, A_z; three anglar rates p, q, r; two incidence angle α and β; airspeed V, and altitude h.

Inference engine: The function of inference engine is to isolate failures and make flight decision on the basis of knowledge base and data base combining the decision of flight commander. In order to judge between measured output fault and computed output fault, the other instrumentation errors should be checked further.

(1) When the residual of airspeed V surpasses the threshold, θ, α, β, ϕ, and h should be checked.

(2) When the residual of angle-of attack α surpasses the threshold, θ, u, w, ϕ, and h should be checked.

(3) When the residual of sideslip angle β surpasses the threshold, θ, ϕ, u, v, ψ and h should be checked.

(4) When the residual of altitude h surpasses the threshold, θ, u, v, w, and ϕ should be checked.

(5) When the residual of pitch angle θ surpasses the threshold, q, r, and Φ should be checked.

(6) When the residual of roll angle Φ surpasses the threshold, p, q, r, and θ should be checked.

(7) When the residual of yaw angle ψ surpasses the threshold, θ, q, r, and Φ should be checked.

(8) When the residuals of three accelerations surpass the threshold, V, u, v, w should be checked.

(9) When the residual of roll rate p surpasses the threshold, V, v, w, and Φ should be checked.

(10) When the residual of pitch rate q surpasses the threshold, θ, u, w, α, Φ, ψ, and h should be checked.

(11) When the residual of yaw rate r surpasses the threshold, θ, u, v, β, Φ, and ψ should be checked.

For example, if the fault of computed pitch angle were caused by the fault of pitch rate, the residuals of Φ, u, w, and ψ should all surpass the corresponding thresholds; otherwise the sensor of pitch rate would be unfaulty.

The basic structure of FDI for flight test system is show in Fig. 1.

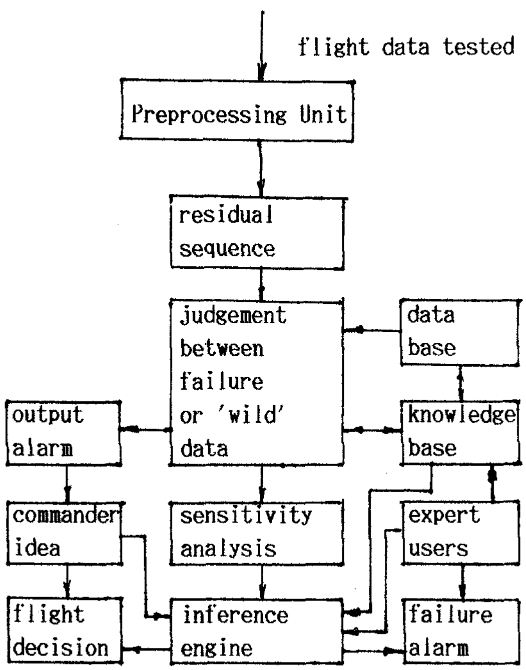

Fig. 1. Basic Structure of Expert System for FDI of flight.

In Fig. 1 the residual sequence is generated in bias-separated estimator.

Application of state estimation method to the residual generation of FDI for aircraft is posible because the forces and resulting motions of an along a flight path are related by well-known equations of motion. The equations may be used to produce estimates of force and motion variables that can be compared with corresponding measurement time-histories. Therefore state estimation technique is used in this paper to generate signal of failures of sensor for aircraft.

III. Model for Flight State Estimation

The mathematical model used for flight state estimation is described, in general, by three sets of kinematic equations with the state variables consisting of three linear velocities u, v, and w; three position angles θ, Φ, and ψ; and altitude h. The input variables in the equations are the linear accelerations A_x, A_y, A_z and anglar rates p, q, r. The kinematic equations are formulated as

$$\left.\begin{aligned}
\dot{u} &= -qw+rv-g\sin\theta+A_x \\
\dot{v} &= -ru+pw+g\sin\Phi\cos\theta+A_y \\
\dot{w} &= -pv+qu+g\cos\Phi\cos\theta+A_z \\
\dot{\psi} &= (r\cos\Phi+q\sin\Phi)/\cos\theta \\
\dot{\theta} &= q\cos\Phi-r\sin\Phi \\
\dot{\Phi} &= p+(q\sin\Phi+r\cos\Phi)\tan\theta \\
\dot{h} &= u\sin\theta-v\sin\Phi\cos\theta-w\cos\theta\cos\Phi
\end{aligned}\right\} \quad (1)$$

Since all variables are sampled, a discrete-time filter will be applied to process the measurements. Usually, the nonlinear equations (1) are first linearized and then transformed into discrete-time versions. Big modelling errors may often appear when aircraft maneuvers. In order to decrease modelling errors, this present paper introduces a exact discrete-time model for state estimation.

Integrating equations (1), we obtained the exact discrete-time model.

$$X_{1,k+1} = X_{1,k} - F^T \int_{kT}^{(k+1)T} A^T \Phi(t,kT)\, dt\, X_{2,k} - gF^T \int_{kT}^{(K+1)T} A^T \int_{kT}^{\tau} \Phi(t,\tau)\,(u_1+AF)\, d\tau\, dt$$

$$X_{2,k+1} = \Phi[(k+1)T,kT]\, X_{2,k} + g\int_{kT}^{(K+1)T} \Phi[(k+1)T,t](u_1+AF)dt \qquad (2)$$

$$\theta_{k+1} = \theta_k + \int_{kT}^{(K+1)T} [q,r]\, B\, dt\, C$$

$$\phi_{k+1} = \phi_k + \int_{kT}^{(K+1)T} (p\, dt + \tan\theta\, B\, dt\, C)$$

$$\psi_{k+1} = \psi_k + \int_{kT}^{(K+1)T} B/\cos\theta\, dt\, C$$

where $\Phi(t,\tau)$ is the state-transition matrix of

$$\dot{X} = E\,X$$

and

$$E = \begin{bmatrix} 0 & r & -q \\ -r & 0 & p \\ q & -p & 0 \end{bmatrix}$$

$$X_1 = h$$

$$X_2 = [\, u,\ v,\ w\,]^T$$

$$X_3 = [\, \theta,\ \phi,\ \psi\,]^T$$

$$u_1 = [\, n_x,\ n_y,\ n_z\,]^T$$

$$u_2 = [\, p,\ q,\ r\,]^T$$

$$F^T = [\, \cos\theta_k, \sin\theta_k \sin\phi_k, \sin\theta_k \cos\phi_k\ \ -\sin\theta_{,k}, \cos\theta_k \sin\phi_k, \cos\theta_k \cos\phi_k]$$

$$A = \begin{bmatrix} 1 & 0 \\ 0 & B^T \end{bmatrix} [\, -l\sin\Delta\theta_k,\ l\cos\Delta\theta_k\,]$$

$$B = \begin{bmatrix} \cos\Delta\phi_k & -\sin\Delta\phi_k \\ \sin\Delta\phi_k & \cos\Delta\phi_k \end{bmatrix}$$

$$C = \begin{bmatrix} \cos\phi_k \\ \sin\phi_k \end{bmatrix}$$

$$\Delta\theta_k = \theta - \theta_k$$

$$\Delta\phi_k = \phi - \phi_k$$

It is considered that the following variables are measured:

(1) The inputs to the system A_x, A_y, A_z ($A_x = g\, n_x$, $A_y = g\, n_y$, $A_z = g\, n_z$), p, q, and r;

(2) The airspeed V, two incidence angles α and β, three position angles θ, ϕ, and ψ, and altitude h (these variables represent the outputs of the system).

The measured variables are corrupted by systematic and random errors. It is, therefore, assumed that

$$u_1 = (\, I + \Lambda_1)\, u_{1,m} + b_{u1,m} + \eta_1 = \bar{u}_1 + \eta_1$$

$$u_2 = (\, I + \Lambda_2)\, u_{2,m} + b_{u2,m} + \eta_2 = \bar{u}_2 + \eta_2$$

where u_1 and u_2 are the true values of the inputs, Λ_1 and Λ_2 the unknown scale factor matrices, b_{u1} and b_{u2} the constant biases, and η_1 and η_2 the measurement noise vectors, and

$$\Lambda_1 = \mathrm{diag}\,[\, \lambda_x,\ \lambda_y,\ \lambda_z\,]$$

$$\Lambda_2 = \mathrm{diag}\,[\, \lambda_p,\ \lambda_q,\ \lambda_r\,]$$

$$b_{u1} = [\, b_x,\ b_y,\ b_z\,]^T$$

$$b_{u2} = [\, b_p,\ b_q,\ b_r\,]^T$$

Substitution of equations into equation (2) yields the discrete-time model for the state estimation:

$$X_{k+1} = M_{k+1,k}\, X_k + u_x(u_1,\ u_2) + B_k\, b + \Gamma_k \int_{kT}^{(K+1)T} \begin{bmatrix} \eta_1 \\ \eta_2 \end{bmatrix} dt \qquad (3)$$

where

$$X^T = [\ \Delta h,\ u,\ v,\ w,\ \theta,\ \phi,\ \psi\ ]$$

$$M_{k+1,k} = \begin{pmatrix} 1 & f_{12} & f_{13} \\ 0 & \Phi[(k+1)T, kT] & f_{23} \\ 0 & 0 & f_{33} \end{pmatrix}$$

$$u_x = [\ u_{x1}(\bar{u}_1)^T,\ u_{x2}(\bar{u}_1,\bar{u}_2)^T,\ u_{x3}(\bar{u}_2)^T\ ]^T$$

$$b = [\ b_{u1}^T,\ b_{u2}^T, \lambda_x, \lambda_y, \lambda_z, \lambda_p, \lambda_q,\ \lambda_r]^T$$

u_x is not relevant to the states; f_{12}, f_{13}, f_{23}, f_{33}, may be carried out from the equation (2).

The output equations take the forms

$$Y_{im} = h_i(\ X_i, u_1,\ u_2,\ b_i\ ) + V_i \qquad i=1,2,3 \tag{4}$$

where $y_1 = h$

$$y_2 = [\ V_G,\ \beta,\ \alpha\ ]^T$$

$$y_3 = [\ \theta,\ \phi,\ \psi\ ]^T$$

$$b_1 = [\ b_h,\ \lambda_h\ ]^T$$

$$b_2 = [\ b_v, b_\alpha\ , b_\beta\ ,\ \lambda_v,\ \lambda_\alpha\ ,\ \lambda_\beta\ ]^T$$

$$b_3 = [\ b_\theta\ \ , b_\phi\ \ , b_\psi\ ]^T$$

and

$$V = [\eta_h, \eta_v, \eta_\alpha\ , \eta_\beta\ , \eta_\theta\ , \eta_\phi\ \ ]^T$$

Letting $\xi_k = \int_{kT}^{(k+1)T} \begin{pmatrix} \eta_1 \\ \eta_2 \end{pmatrix} dt$

and assuming

$$E\{\xi_k\} = 0\ , \qquad E\{\ V_k\} = 0$$

$$E\{\xi_k\ \xi_j^T\} = \delta_{kj} Q_k$$

$$E\{\ V_k\ V_j^T\} = \delta_{kj} R_k$$

$$E\{\ V_k\ \xi_j^T\} = 0$$

equations (3) and (4) can be used for the state estimation and residual generation.

IV. Method for Robust Residual Generation

The technoque of state estimation may provide both a check on instrument accuracy and data consistency, and estimates of unmeasured or poorly measured variables. Over the past few years, this work in the field has been evolving toward the use of more complete kinematic models, the development of more sophisticated algorithms, and the treatment of more difficult applications. Since the measurements often may contain significant errors which must de identified before the data are used in residual generation for FDI.

Usually, the biases and scale errors are considered as components of a so-called augmented state vector in the most methods of flight state estimator. In the augmented-state implementation the overall process is of the order n1+n2 , where the number of dynamic variables (i.e., the dimension of X) is n1, the number of biases (the dimension of b) is n2, and the n1+n2 variables are all coupled, in the filter and in the covariance matrix propagation. Evidently, it is too difficult for this approach to achieve real-time flight state estimation. In the bias-separated implementation (Friedland, 1983), the maximum dimension one needs to be concerned with is the larger of n1 or n2, and errors in the estimation of the biases do not contaminate the estimation of the bias-free estimate of the dynamic state. Theoretical study and actual application show that the bias-separated filter implementation would require fewer numerical operation than the augmented-state one and may be to avoid numerical ill-conditioning. For this reason, separated bias identification and state estimation method would be chosen as the basic algorithm of real-time flight state estimation and residual generation.

Since the matrix $M_{k+1,k}$ of equation (3) is upper trianglar, hierarchical techniques are used in this present paper to get high computational efficiency.

Letting $\quad b_1 = b_1$

$$b_2 = [\ b_{u1}, b_2, \lambda_x, \lambda_y, \lambda_z]^T$$

$$b_3 = [\ b_{u2}, b_3, \lambda_p, \lambda_q, \lambda_r]^T$$

Expanding the nonlinear equation (4) in Taylor series expansion, we obtained

$$Y_{i,k+1} = H_{i,k+1}X_{i,k+1}+D_{i,k+1}b_i+ e_{i,k+1} + V_{i,k+1} \tag{5}$$

where the matrices $H_{i,k+1}$ and $D_{i,k+1}$ are defined by

$$H_{i,k+1}=\frac{\partial h_i(X_i,u_1, u_2, b_i)}{\partial X_i}\Big|_{X_{i,k+1},b_k,}$$

$$D_{i,k+1}=\frac{\partial h_i(X_i,u_1, u_2, b_i)}{\partial b_i}\Big|_{X_{i,k+1},b_k,}$$

$$i=1,2,3$$

and

$$e_{i,k+1} = h_i(X_i,u_1, u_2, b_i)-H_{i,k+1}X_{i,k+1} -D_{i,k+1}b_i$$

Thus on the basis of stochastic vector difference equation (3) and measurement equation (5), flight state and biases can be estimated by using separated bias identification and state estimation algorithm.

The time update equations are

$$b_{i,k+1/k} = b_{i,k}$$

$$P_{bi,k+1} =P_{bi,k/k} \tag{6}$$

$$X_{k+1/k}= M_{k+1,k}X_{k/k}+u_x(u_1, u_2)+B_{k+1}b_k$$

$$P_{k+1/k}=M_{k+1,k}P_{0,k/k}M_{k+1,k}^T+\Gamma_k Q_k \Gamma_k^T$$

$$i=1,2,3$$

The measurement update of bias-free state estimates

$$X_{0i,k+1/k+1}= X_{i,k+1/k}+K_{0i,k+1}\, e_{i,k+1}$$

$$K_{oi,k+1}=P_{0i,k+1}H_{i,k+1}R_i^{-1}{}_{k+1} \tag{7}$$

$$P_{oi,k+1}=(1-K_{0i,k+1}H_{i,k+1})P_{oi,k+1/k}$$

$$i=1,2,3$$

The measurement update of b

$$b_{i,k+1}= b_{i,k}+K_{bi,k+1}\, e_{i,k+1}$$

$$K_{bi,k+1}=P_{bi,k+1/k+1}(H_{i,k+1} V_{bi,k/k-1}+D_{i,k+1})^T R_i^{-1}{}_{k+1} \tag{8}$$

$$P^{-1}{}_{bi,k+1/k+1}= P^{-1}{}_{bi,k/k}+C^T{}_{k+1/k}(H_{i,k+1} P_{0i,k+1/k}H_{i,k+1}{}^T+R_{i,k+1})^{-1} C_{i,k+1/k}$$

$$i=1,2,3$$

where

$$C_{i,k+1}=H_{i,k+1}U_{i,k}+D_{i,k+1}$$

$$U_{i,k}=M_{i,k+1,k}V_{bi,k/k-1}+B_{i,k}$$

$$V_{bi,k+1/k}=U_{i,k}-K_{0i,k+1}C_{i,k+1}$$

$$e_{i,k+1} = y_{im,k+1}- h_i(X_{i,k+1/k},u_1,u_2,b_{i,k})$$

$$i=1,2,3$$

and

$$M_{1,k+1,k} = 1$$

$$M_{3,k+1,k} = f_{33}$$

$$M_{2,k+1,k}= \Phi[(k+1)T,kT]$$

The measurement update of X_i

$$X_{i,k+1/k+1}= X_{0i,k+1/k+1}+ V_{bi,k+1/k}K_{bi,k+1}\, e_{i,k+1} \tag{9}$$

In the equations (6)--(9) subscript ' 0 ' represents the ' bias-free ' state estimator and subscript ' b ' bias estimator; $X_{i,k+1/k}$ can also be calculated by using numerical integration of Runge-Kutta type.

The state estimation error equations can be written as follows

$$E_{i,k+1}=M_{i,k+1,k}E_{i,k}+ S_{k+1} -(K_{0i,k+1}+V_{bi,k+1/k})\, E_{i,k} \tag{10}$$

where

$$S_{k+1} = \text{sign}(E_{.i.k+1})\, b^T_{i.k} b_{i.k}$$

V. Simulation and Application

The expert system for the FDI of flight test system has been simulated in flight data acquisition system. The results of simulation and actual application show that the estimator of flight state can give robust residual generation and the expert system can declare the faulty and locate failures correctly. Some applications of the flight test of high angle-of-attack show that this expert system is suitable to the flight regimes of both low and high angle-of attack. Fig. 2 shows the result of FDI for flight test carried out by the expert system presented in this present paper.

VI. Conclusion

An expert system for FDI of aircraft is presented in this paper. The new method has been simulated in Chinese Flight Test Center. Various applications show that the expert system can correctly declare the faulty and locate the failures. For more experienced users this expert system may be improved further.

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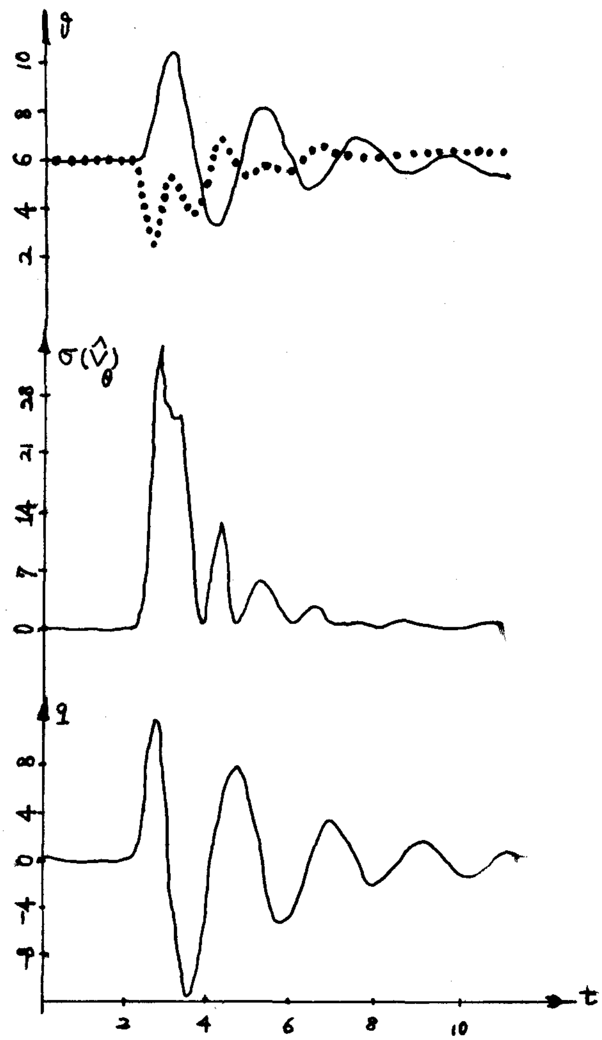

Fig. 2. Result of FDI of Expert System for Aircraft (t=2.3 second, alarm is released).