# HETERO-REDUNDANT ARCHITECTURE WITH KALMAN FILTER FOR INPUT PROCESSING IN FLIGHT CONTROL SYSTEM

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## Abstract

In order to obtain the required reliability level, current practice in the architectural design of Flight Control Systems (FCSs) for modern fighter aircrafts is to incorporate multi-redundant channels of similar type. Problems encountered with this architecture are due to common mode failure, instantaneous sensor-failure, inadequate filtering etc. Aiming to achieve better performance and reliability, a **Hetero-redundant architecture** for input processing with Kalman filter in one channel and numerical and conventional methods in other channels, has been proposed in this paper. The architecture, and use of Kalman filter techniques for input processing and its performance evaluation through simulation are presented in this paper. Studies show that in the proposed architecture common mode failures are avoided and the effect of instantaneous sensor-failure will be less than that for homogeneous redundant system. Output values estimated by Kalman Filter closely follow actuals, maximum steady state error being ±1.5%, and commands based on these values generate good response. An implementation scheme with two processors is also discussed.

## 1.0 Introduction

New performance demands are continuously imposed on Flight Control System (FCS) of modern fighter aircraft at a rate which subdues the potential for reliability improvements of these systems. These include extended flight regimes for multi-mission capabilities achieved through operational modes such as command and stability augmentation, load alleviation, auto landing, etc. The Flight Control Computer (FCC) being the central component of FCS, its design necessitates incorporation of sound fault tolerant approaches to obtain the required level of reliability. Due to the reliability characteristics of electronic hardware and software, most of the current FCC architectures incorporate multiple redundancy. But they do not handle problems such as common mode failures, instantaneous sensor-failures etc. Hence, the search continues for new fault tolerant approaches to circumvent these problems. In this context, we have examined the possibility of improving the reliability and performance of a quadruplexed FCS through a hetero-redundant architecture for its input processing sub-system. This paper presents (i) hetero-redundant architecture for input processing with Kalman filter in one of its channels, (ii) formulation of Kalman Filter for input processing, and (iii) its performance evaluation through digital flight simulation. Based on the current practices in VLSI, a realization scheme for Kalman Filter is also drawn as described in section 5.0.

## 2.0 Flight Control System Architecture

The flight control systems of modern fighter aircraft consist of sensors, FCCs, servo-actuators and displays. The functions of FCC are data-acquisition through sensors, data processing to generate control-commands to servo-actuators and parameters for pilot-display. The set of data acquired are of aircraft motion, ambient, pilot-commands and positions of control surfaces. A simplex FCS architecture does not meet the reliability requirements. Hence, the design practice is to provide multiple redundancy in terms of hardware and software components. The redundancy level as well as configuration of each of these component-groups are dictated by the required level of reliability and fault tolerance.

### 2.1 State of Art

In a conventional FCS, all the channels are alike in terms of its hardware and software. Each channel employs a dedicated Data Management Processor (DMP) and Control Function Processor (CFP) to perform input-output functions and control command generation respectively. The input processing in DMP primarily consists of acquisition, coding and formatting of data for control law processing. The DMP also performs redundancy management functions and voting. The CFP performs high level manipulation on voted values as per control laws and generates commands to servo-actuators. The inter-channel communication is limited to logic and data transfer for voting.

One of the critical problems faced with these systems is common mode failure due to near coincident errors. There have been attempts to reduce the risks due to coincident errors by running channels in loose synchronism and incorporation of dissimilar codes.[1,2] The experimental results on dissimilar codes show that the assumption of independence of versions is questionable and hence, the expected improvements in reliability too.[3] Another problem encountered with the conventional systems is due to its vulnerability to instantaneous failures of sensors.

### 2.2 Proposed Architecture

A quadruplex FCS architecture employing heterogeneous hardware and software components which are incorporated at the conceptual stage of design of FCS, has been proposed. The schematic of Hetero-Redundant architecture of FCS is shown in Fig. (1). Each of its channels performs processing of input , control-law and output in different ways. The sub-system for input-processing employs Kalman Filter (KF), two numerical methods viz., Modified Euler (MEU) and Runge Kutta-4 (RK-4) and Conventional (CONV) technique to compute the states of aircraft in four different ways. In each channel boundary-exceedence of flight envelope is identified through a functional module of Boundary Controller (BC). The redundancy management and voting are performed in each channel by a RM/V module.[4] The data computed by an INVC (INVerse Calculation) module is compared with the output of each voter to establish the integrity of voter. An INTP (INTerPolater) module is also employed in each channel to interpolate data such as aerodynamic derivatives, gains etc. stored in look-up tables. Based on the voted outputs, commands for normal and boundary controls are computed by the module of control-law processing in each channel. These commands are routed to the actuators which move the control surfaces to effect the required motion of aircraft.

#### 2.2.1 Why Kalman Filter?

Process control systems use estimation techniques viz., maximum-likelihood, least square, Kalman filter, etc. These techniques are also adopted for applications such as calibration of inertial systems, estimation of aircraft control-parameters etc.[5]

Each of the input processing techniques viz., MEU, RK-4, CONV and KF ,is different from the others. MEU and RK-4 compute the states by solving a system of differential equations, taking only the initial values of states to start with. Conventional technique employs direct measurement of state variables with limited filtering, normally, effected through averaging. Whereas, Kalman Filter optimally estimates the state variables. Hence, the occurrence of common mode failures due to near coincident errors could be ruled out.

The conventional input processing sub-systems do not have capability to cope up with instantaneous sensor-failures. Kalman Filter being a Gauss-Markovian process, estimates the states based on prior estimates and the current measurements. The control commands based on these estimates would generate better response. Thus, the effects of instantaneous failures would be less.

In a conventional FCS, the states of the aircraft are measured, averaged and the control commands are generated accordingly. The noise in the measured states would directly affect the performance of the system. Whereas, the Kalman filter estimates the states optimally from the measured data resulting in a better response of aircraft.

Thus, the Kalman Filter renders better advantages to input processing.

#### 2.2.2 Formulation of Kalman Filter as Input Processor

The recursive and discrete nature of Kalman Filter makes it suitable for the estimation of states of an aircraft in real-time. A state-space model of Kalman Filter is described in Appendix-1. Fig. (2) shows the block schematic of Kalman Filter Estimator. The mathematical description of a system given below, forms the basis for estimation of its states.

A dynamic system of discrete, time-varying and recursive type, can be expressed as :

$$X(k+1)= \Phi(k).X(k)+F(k).U(k)+\omega(k) \quad \ldots (1)$$

$$Z(k+1) = H(k+1).X(k+1) + \upsilon(k+1) \quad \ldots (2)$$

Where, X is an (nx1) state vector, U is an (nx1) control vector, $\Phi$ is an (nxn) state transition matrix,F is an (nxl) control influence matrix, Z is an (mx1) observation vector, H is an (mxn) observation matrix and k (= Ø,1,...) is index for discrete time. $\omega$ and $\upsilon$ are independent Zero Mean White Gaussian sequences representing plant noise and measurement noise respectively.

Here, the system is driven by the pilot inputs U(k) which are measured. The state-measurements Z(k) are linearly dependent on the states X(k) of the aircraft. These measurements are made at discrete points in time. Hence, the Kalman filter becomes a discrete time processor on them and estimates the states X(k) at time k. The measurements of U(k) and Z(k) would be invariably corrupted by noise. The noise contents in control-inputs and measurements of states are denoted by $\omega(k)$ and $\upsilon(k)$ respectively. The aircraft with FCS forms a dynamic system. The input processor is modelled as Kalman Filter to estimate the states viz., Angle of Attack ($\alpha$) and pitch rate

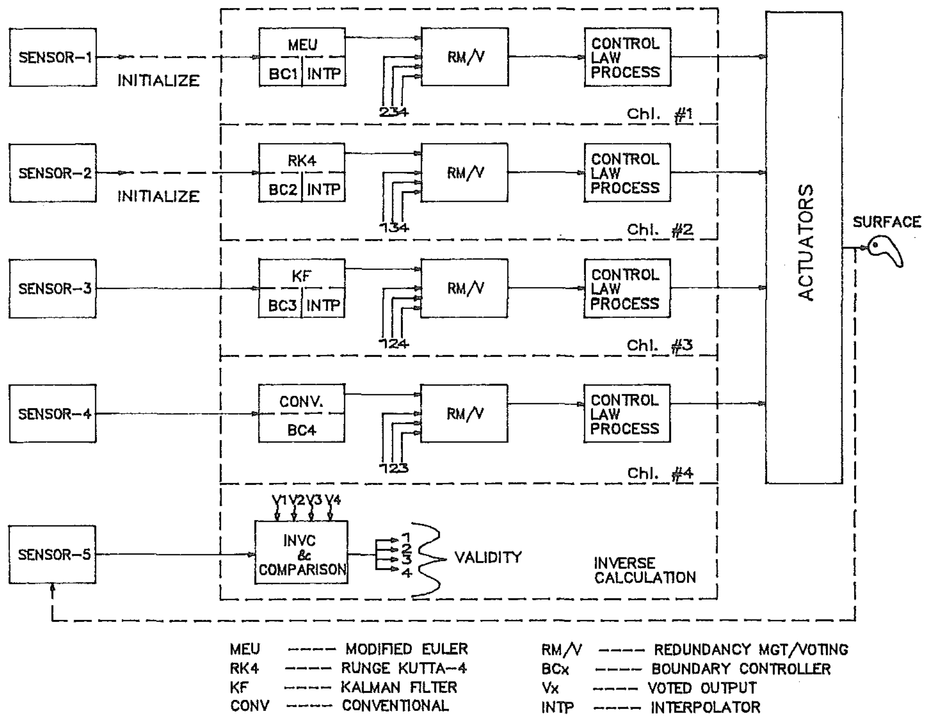



FIG (1) SCHEMATIC OF HETERO–REDUNDANT ARCHITECTURE OF FLIGHT CONTROL SYSTEM

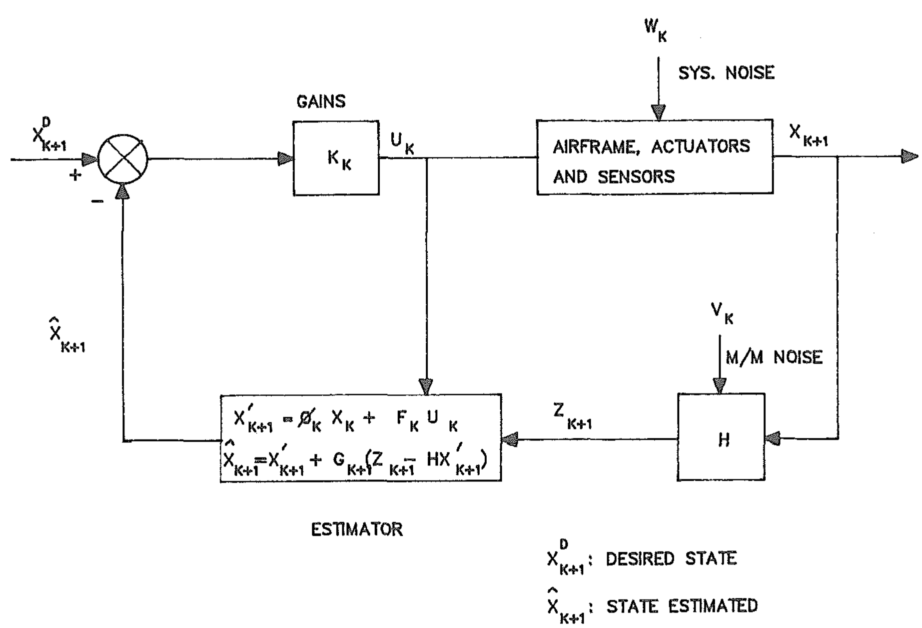



FIG. (2) BLOCK SCHEMATIC OF KALMAN FILTER ESTIMATOR (q), of the aircraft under symmetrical, longitudinal maneuvers. Then, this model is studied under different conditions of flight and pilot inputs.

The mathematical relationships between the states $\alpha$ and q are given by the equations below.

$$\dot{\alpha} = Z_\alpha.\alpha + Z_q.q + Z_{\delta e}.\delta_e \quad ... \quad (3)$$

$$\dot{q} = M_\alpha.\alpha + M_q.q + M_{\delta e}.\delta_e \quad ... \quad (4)$$

Where, $\alpha$ and q are angle of attack and pitch rate respectively. $Z_{()}$ and $M_{()}$ are dimensional derivatives of aircraft and $\delta_e$ is control command to elevator. A controller which generates elevator commands $\delta_e$ as a linear function of the aircraft states $\alpha$ and q, has been deployed. The controller equations under normal and maneuver-limiting conditions are as follows:

$$\delta_e = K1(\alpha-\alpha_D) + K2*q + \delta_{et} \quad ... \quad (5)$$

$$\delta_e = K3(\alpha-\alpha_L) + K4*q + \delta_{et} \quad ... \quad (6)$$

Where, $\delta_e$ is the elevator control command, $\delta_{et}$ is the trim value of elevator command, $K_{()}$s are control gains, $\alpha$, $\alpha_D$ and $\alpha_L$ are the estimated, desired and limiting values of angle of attack respectively.

Then the set of simultaneous differential equations (3) and (4) are transformed from continuous time to discrete time for the Kalman Filter process. These equations can be expressed in vector form as below.

$$\dot{X} = A.X + B.U \quad ... \quad (7)$$

Where, A (2x2) is the system matrix, B (2x1) is the input vector, X (2x1) is the state vector and U is the control input. (.) and T denote rate of change and transpose respectively. Hence, for pitch-axis control,

$$X = [\ \alpha\ q\ ]^T, \quad B = [\ Z_{\delta e}\ M_{\delta e}\ ]^T$$

$$A = \begin{bmatrix} Z_\alpha & Z_q \\ M_\alpha & M_q \end{bmatrix} \quad \text{and} \quad U = [\delta_e].$$

The initial condition $X(\emptyset) = [\alpha_t\ q_\emptyset]^T$ is given.

Then transformations through matrix exponential are performed to get state transition matrix $\Phi$ from system matrix A and control influence vector F from input vector B. Then, these equations are solved following the steps in Appendix-1. The simulation exercises carried out are explained below.

## 3.Ø Flight Simulation

The performance of Kalman filter for input-processing of FCS has been evaluated through simulation exercises on a 6DOF simulation model of a fighter aircraft. These exercises were restricted to symmetrical longitudinal maneuvers. The model has a representation of rigid body dynamics of aircraft, pilot inputs and the channel with Kalman filter for input processing. The types of pilot inputs reckoned for simulation were ramp, step and pulse as per MIL-A-ØØ8861A. The operating points of aircraft were selected to cover the flight envelope at its boundary at low Mach numbers. The state-measurements were synthesized by adding white noise to the states initially generated by simulation. The details of aircraft model, state synthesis and filter model are dealt with in the following sections.

### 3.1 Aircraft Model

The aircraft model is represented by the set of kinematic equations given below.(6)

Forces:

$$\dot{u} = rv-qw-gSin\theta + (\bar{q}S\ C_{xt} + T)/m \quad ... \quad (8)$$

$$\dot{v} = pw-ru+gCos\theta\ Sin\phi + \bar{q}S\ C_{yt}/m \quad ... \quad (9)$$

$$\dot{w} = qu-pv+gCos\theta\ Cos\phi + \bar{q}s\ C_{zt}/m \quad ... \quad (1\emptyset)$$

Moments:

$$\dot{p} = [(I_y - I_z)qr + \bar{q}Sb\ C_{lt}]/I_x \quad ... \quad (11)$$

$$\dot{q} = [(I_z - I_x)pr + \bar{q}S\bar{c}\ C_{mt}]/I_y \quad ... \quad (12)$$

$$\dot{r} = [(I_x - I_y)pq + \bar{q}Sb\ C_{nt}]/I_z \quad ... \quad (13)$$

Where, u,v and w are components of velocity along X,Y and Z axes respectively; p,q and r are roll, pitch and yaw rates; $I_x$,$I_y$ and $I_z$ are moments of inertia about X,Y and Z axes respectively and $I_{xz} = \emptyset$. $C_{xt}$,$C_{yt}$ and $C_{zt}$ are total force coefficients along X,Y and Z axes and $C_{lt}$,$C_{mt}$ and $C_{nt}$ are rolling ,pitching and yawing moment coefficients. $\bar{q}$,S,b,$\bar{c}$,m,T and g are dynamic pressure , wing area, wing span, mean aerodynamic chord, mass, thrust and acceleration due to gravity respectively. $\phi$ and $\theta$ are Euler angles.The dot (.) represents the derivative.

### 3.2 State-Synthesis

The measured states Z(k) were synthesized by adding white noise components to the values of states X(k) obtained by exercising the 6 DOF model of aircraft, as follows:

$$Z(k)=X(k)+N.RAN\ [S(k),S(k-1)] \quad ... \quad (14)$$

Where, N is the gain coefficient and RAN[...] is a function of random number S(k) which is normally distributed.

### 3.3 Kalman Filter Model

The states of the aircraft ,namely $\alpha$ and q, were estimated by the Kalman filter . The noise elements contained in these states were assumed to be Zero Mean White Gaussian. The R matrix has been formed with diagonal elements as the square of standard deviations of state parameters $\alpha$ and q viz., $\{\sigma_\alpha\}$ and $\{\sigma_q\}$. The elements of matrices $\Phi$ and F which depend on flight condition,have been pre-computed and stored. For the flight conditions not stored, the elemental values of these matrices are interpolated. The matrix H is also stored apriori. Based on practical considerations the sample time is fixed as 2Ø msec. The state covariance matrix P is initialized based on the estimate of initial state noise. The initial values of the states $\alpha$ and q were set to be trim value of $\alpha$ denoted by $\alpha_t$ and zero respectively.

### 3.4 Scenarios of Simulation

The studies were conducted under the simulated flight conditions viz., (SL,Ø.7M), (5ØØØm,Ø.7M), (1ØØØØm,Ø.8M) and (15ØØØm,Ø.8M), which cover the flight envelope at its low Mach number-boundary. The pilot commands simulated were ramp, step and pulse, the amplitude of each being varied as per MIL - A - ØØ8861A and limited to a maximum of 6 deg. The instantaneous sensor-failures were simulated by setting the measured data to zero at the instances of failure. The Kalman Filter estimates the states through out the simulation period including these instances. The standard deviations of noise in the measurements of $\alpha$ and q are taken as Ø.29 deg. and Ø.489 deg/sec. respectively.

## 4.Ø Results

The values of states of $\alpha$ and q, both measured and estimated, under the conditions of flight viz., (SL,Ø.7M), (5ØØØm,Ø.7M), (1ØØØØm,Ø.8M) and (15ØØØm,Ø.8M), and pilot inputs were computed and stored during the simulation run. The plots of time histories of states $\alpha$ and q, are given in Figs. (3) through (1Ø) under normal conditions of FCS. The duration of simulation run and hence, that of plots has been fixed as 1Ø Sec. which is adequate to observe the short period behaviour of the aircraft. The measured values and the corresponding estimates from the Kalman Filter are shown by broken and continuous lines respectively. The following are the observations based on these plots.

i) The filter minimizes the noise contents in the measured values of states and smoothens it out.

ii) The estimated values closely follow the measured values.

iii) The variations of $\alpha$ and q are better and smoother with Kalman Filter compared to those with conventional technique based on measured values of states. Normally, the short period response of the aircraft is gauged from the variations of $\alpha$ and q. Hence, the quality of response of the aircraft with Kalman Filter is better than that with conventional technique.

iv) The maximum error under steady state conditions is of the order of ±1.5%.

Figs. (11) and (12) show the time histories of $\alpha$ and q under the normal condition and instantaneous failure of angle of attack sensor respectively. At the instant of failure, the ratio of the reduction in the value of angle of attack under Kalman filter to that under conventional case is Ø.4 . The ratio of the error due to deviation of the estimated value from the actual at the instant of failure to that under steady state condition is of the order of 4. The estimated values of $\alpha$ from Kalman Filter have been found to be closer to the previous estimated values compared to the conventional case where it has dipped to zero. With Kalman filter, the maximum error occurred at the time of occurrence of the sensor failure. When the sensor recovered from the failure, the estimated values also recovered but at a slower rate compared to the conventional case thus, making the transitions smoother. This indicates that even under conditions of instantaneous failure of sensors the aircraft response with Kalman Filter is better and smoother than that with conventional technique.

## 5.Ø Realization Scheme

Due to the rapid advancements in the VLSI circuits, fast processors and memories are available and this has lead to the realization of real-time Kalman filter and supporting modules. The realization of Kalman filter for real-time data processing of this nature has been, in general, limited by the relatively complex mathematical operations necessary in computing estimates through Kalman filter algorithms.[7] With the rapid developments of VLSI circuits, it has become technologically feasible to realize Kalman filter for real-time processing of this type. Out of the many proposed architectures, the one with two dedicated hardware processors has been proposed.[7,8,9,1Ø,11,12] These processors would carry out all the required computational tasks to be performed by Kalman filter. The computations are cyclically performed through an ordered set of steps. In order to avoid delay between cycles of computation, the new data could be shifted into the array from the top, row by row as the calculation proceeds.

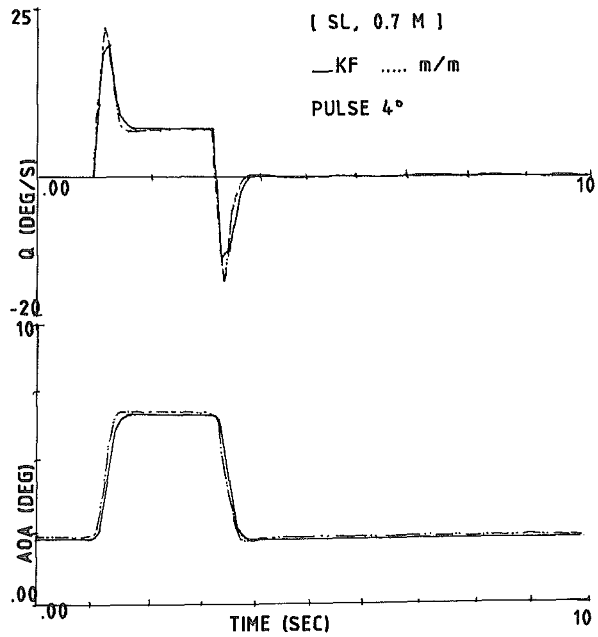



FIG (3)

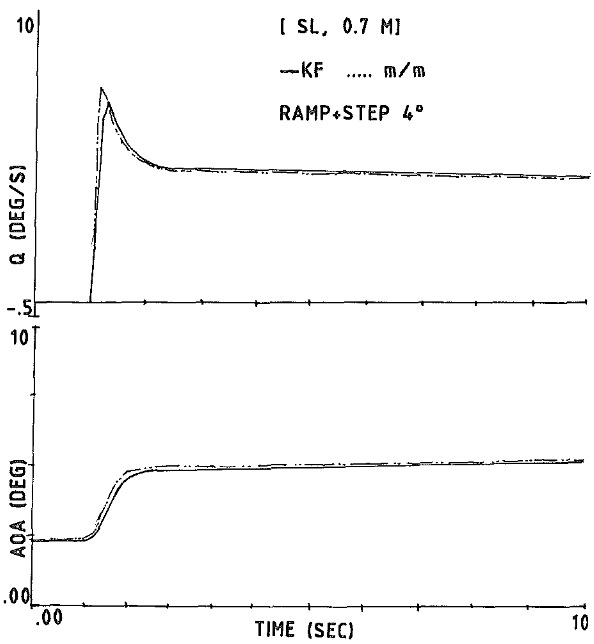



FIG (4)

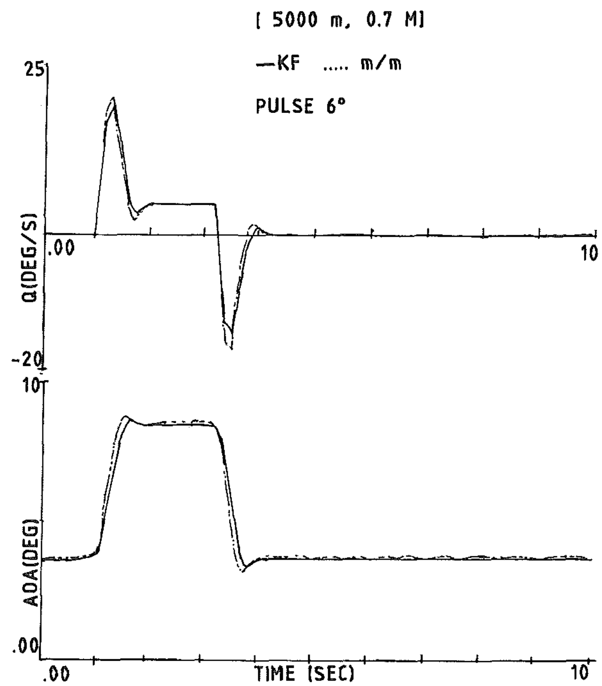



FIG (5)

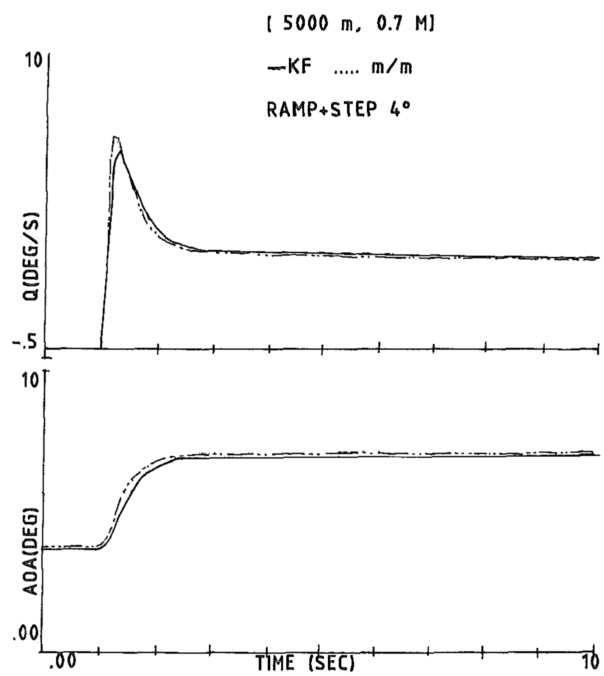



FIG (6)

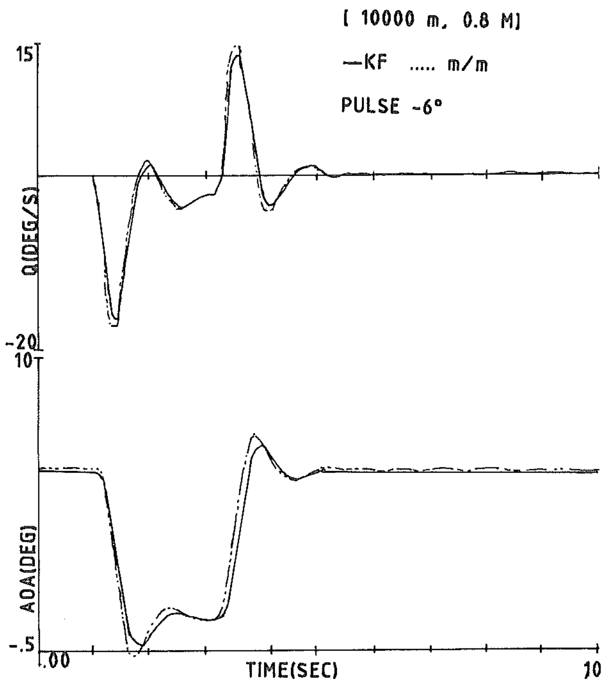
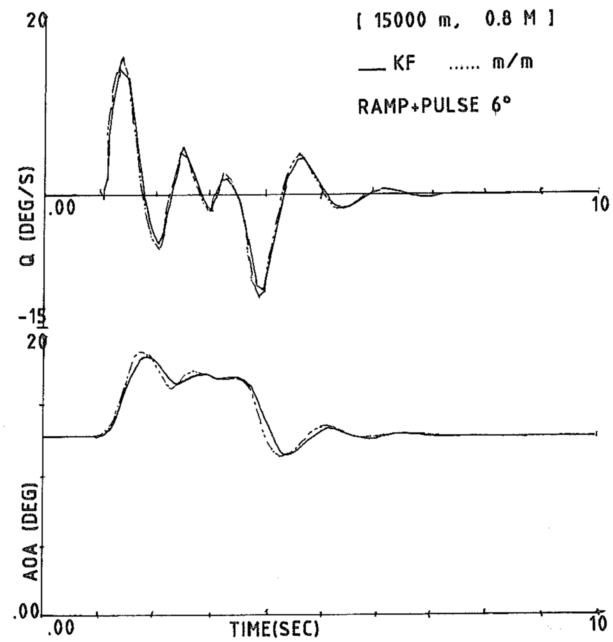



FIG (7)

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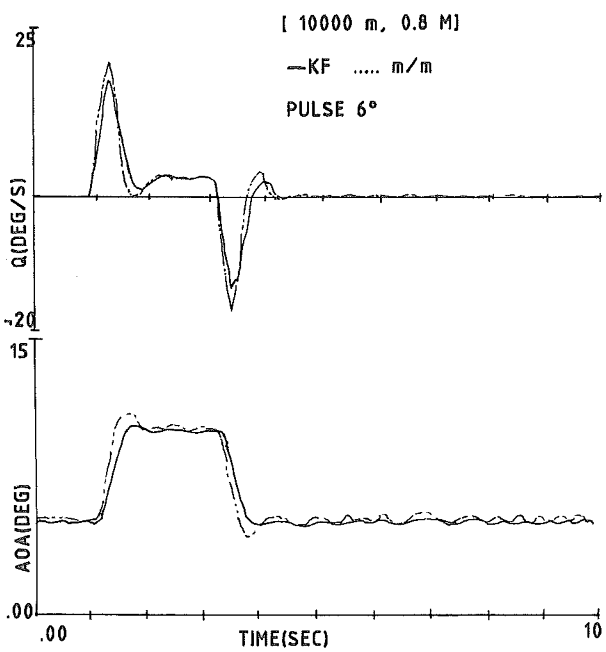


FIG (8)

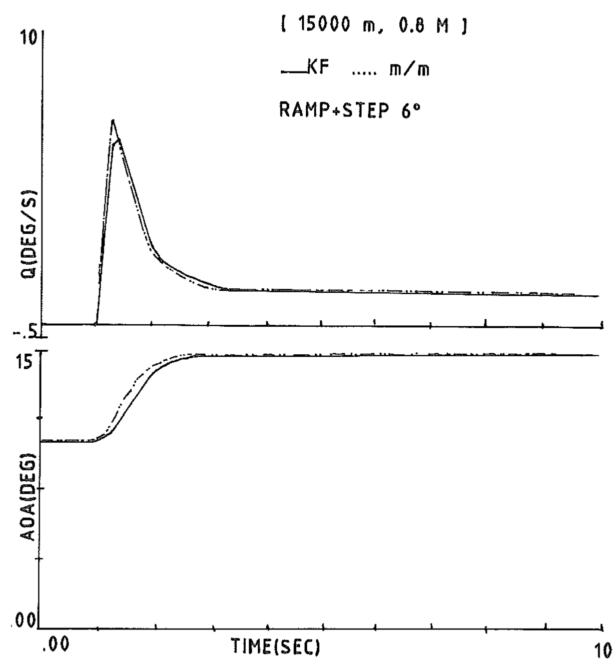


FIG (10)

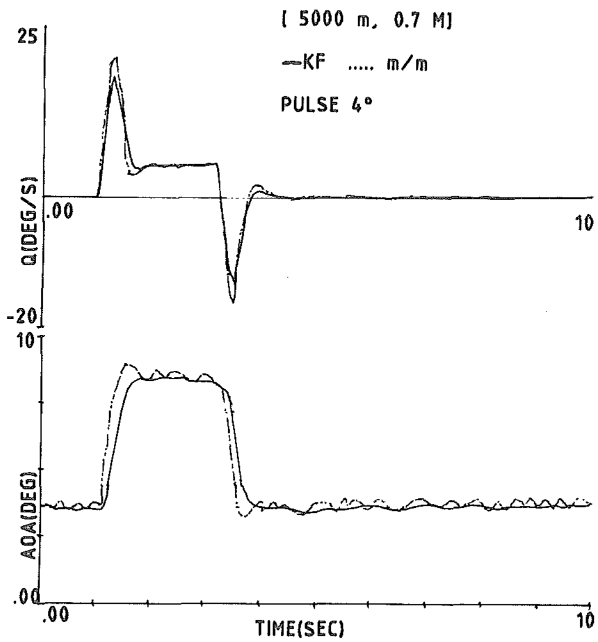


FIG (11)

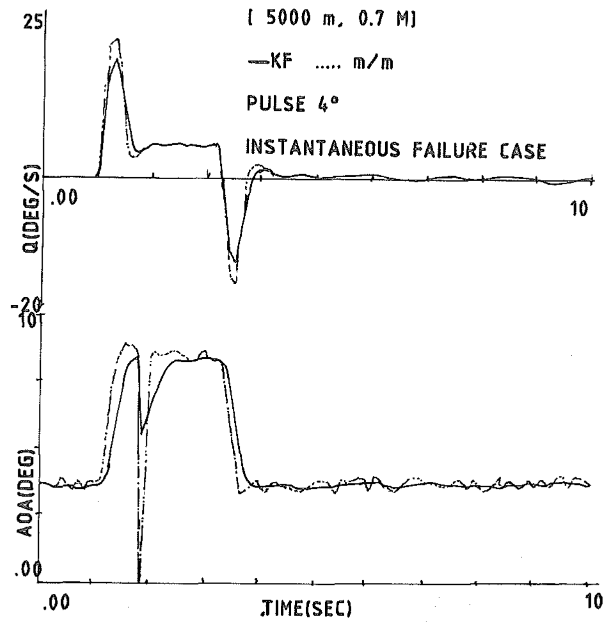


FIG (12)

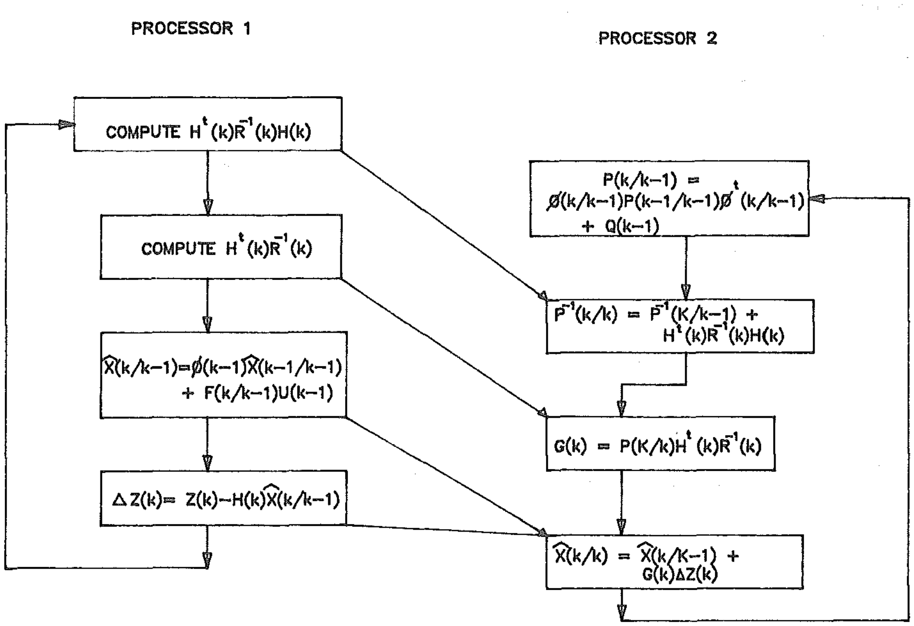


FIG (13) TWO PROCESSOR COMPUTING FLOW DIAGRAM

The flow model employing two processors based on VLSI approach of Yeh is shown in Fig. (13).[7,13] Processors 1 and 2 perform computations indicated inside the rectangular blocks as per the algorithm given in Appendix-2. Fig. (14) shows the block schematic of Kalman filter used for the estimation of timings. The total time taken by one cycle is estimated to be 13Ø μs which is well within the allowable time limits.

## 6.Ø Conclusions

The proposed hetero-redundant architecture with Kalman Filter for input processing avoids common mode failures due to reasons discussed in section 2.2.1. The Kalman Filter minimizes the noise content in the measured values and smoothens it out which results in optimal control commands rendering good aircraft response. The results under different conditions of flight and pilot inputs viz., ramp, step and pulse, show that the estimated values closely follow the measured values. The maximum steady state error of the estimated value with respect to actuals is of the order of ±1.5%. Under the conditions of instantaneous sensor-failures, the ratio of the reduction in the value of a estimated by Kalman filter to that obtained under conventional technique was of the order of Ø.4 . This shows that the filter has the capacity even to minimize the effects of instantaneous sensor-failures. Thus, the proposed architecture with Kalman filter in one of its channels renders better performance and reliability. The recent advancements in VLSI Circuits have made the real-time realization of the scheme feasible.

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## Appendix-1 Kalman Filter Model

The Kalman filtering problem can be stated as follows :

$$\hat{X}(k|k-1) = \Phi(k|k-1)X(k-1|k-1) + F(k|k-1)U(k-1|k-1) \quad \ldots (I.1)$$

$$P(k|k-1) = \Phi(k|k-1)P(k-1|k-1)\,\Phi^T(k|k-1) + Q(k-1) \quad \ldots (I.2)$$

$$G(k) = P(k|k-1)H^T(k)[H(k)P(k|k-1)H^T(k) + R(k)]^{-1} \quad \ldots (I.3)$$

$$\hat{X}(k|k) = X(k|k-1) + G(k)\,[\,Z(k) - H(k)X(k|k-1)] \quad \ldots (I.4)$$

$$P(k|k) = [I-G(k)H(k)]\,P(k|k-1) \quad \ldots (I.5)$$

On simplification by substitution from (I.5), equation (I.3) becomes,

$$G(k) = P(k|k)H^T(k)\,R^{-1}(k) \quad \ldots (I.6)$$

Where , P and G are state covariance and Kalman gain matrices respectively. Equations (I.2) and (I.5) are referred to as time updates and equations (I.1) to

(I.4) are referred to as measurement updates. In equation (I.1), the last estimate is projected forward using the dynamics of the equation model. Equations (I.2) and (I.5) give the error covariances necessary to calculate the gain matrices. Equation (I.3) gives the Kalman gain matrix for updating. In equation (I.4), this estimate is updated using the new observation Z(k).

## Appendix-2 Steps of Algorithm

The steps of algorithm for implementation of equations I.1 through I.6 of Appendix - 1, are given below :

Step 1

$$\hat{X}(k|k-1) = \Phi(k|k-1)\ \hat{X}(k-1|k-1) + F(k|k-1)\ U(k-1)$$

Step 2

$$P(k|k-1) = \Phi(k|k-1)\ P(k-1|k-1)\ \Phi^{T}(k|k-1) + Q(k-1)$$

Step 3

Compute $H^{T}(k)\ R^{-1}(k)$

Step 4

Compute $P^{-1}(k|k-1)$

Step 5

$$P^{-1}(k|k) = P^{-1}(k|k-1) + H^{T}(k)\ R^{-1}(k)\ H(k)$$

Step 6

$$G(k) = P(k|k)\ H^{T}(k)\ R^{-1}(k)$$

Step 7

$$\Delta Z(k) = Z(k) - H(k)\ \hat{X}(k|k-1)$$

Step 8

$$\hat{X}(k|k) = \hat{X}(k|k-1) + G(k)\ \Delta Z(k)$$

The results of each step need to be stored for use in latter steps as new entries.

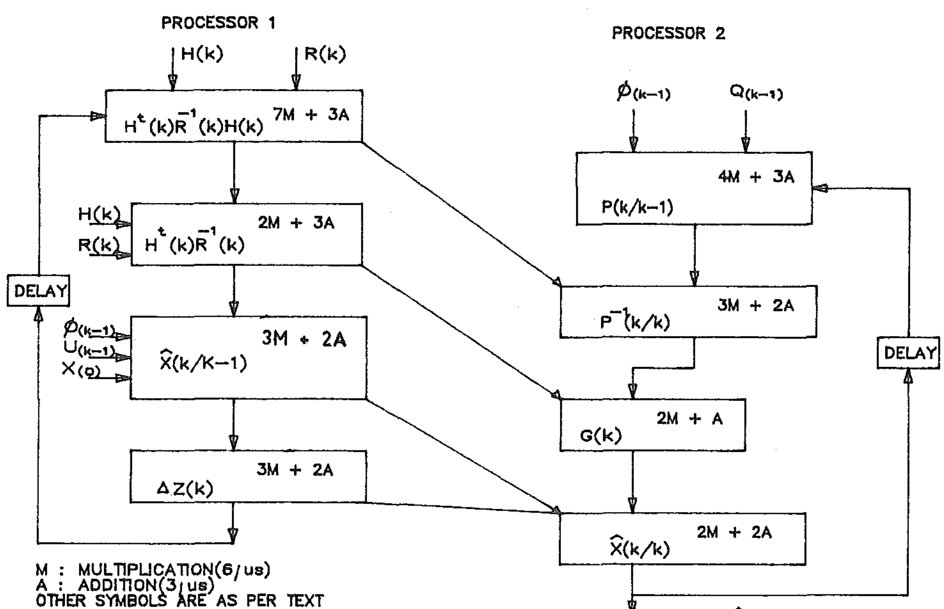


FIG. (14) TIMING — BLOCK DIAGRAM