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Diagnosis of Incipient Sensor Faults in a Flight Control Actuation System

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Abstract: This paper presents a scheme for fault diagnosis in a flight control actuation system. The electromechanical control actuator considered here is based on a DC torque motor. The scheme utilizes the analytical redundancy that exists in the system between the linear actuator position, motor shaft angular velocity and motor current for diagnosis of incipient sensor faults in the system. Fault diagnosis is done using a single Kalman filter, which is driven by the motor shaft velocity sensor. Diagnosis of bias and scale factor faults in the position and current sensor is carried out using structured residuals that are generated using the Kalman filter estimates. Bias and scale factor errors in the velocity sensor are detected using the statistical properties of the innovation sequence of the Kalman filter. In the event of fault in the position sensor, real time reconfiguration using an estimate of the position from the Kalman filter is used for continued operation of the system. Robustness of the scheme to parameter variations is also examined.

Keywords: Fault diagnosis, DC motor, Actuator, Kalman filter

1. INTRODUCTION

Control actuators are widely used in the aerospace industry in the flight control system of aircrafts, missiles and launch vehicles. Faults in the sensors used as feedback elements in control actuation systems can cause serious degradation in system performance. Effective detection and isolation of sensor faults in control actuation systems is vital for enhanced vehicle safety and accomplishment of the intended mission. Detection of incipient (slowly developing) sensor faults is essential for initiating maintenance action to prevent total failure of the system.

Sensor fault detection in dynamic systems has traditionally been achieved using hardware redundancy where three or more sensors are used for measuring the same variable. The outputs of these sensors are monitored by a logic circuit which declares that a sensor is faulty if its signal deviate too far from the average value of the others. The modern approach to sensor fault detection is based upon the idea that three (or more) dissimilar sensors measuring different variables, and therefore producing entirely different signals, can be used in a comparison scheme more sophisticated than simple majority vote logic to detect a fault in one of the set. The rationale for this idea is that even though the sensors are dissimilar they are all driven by the same dynamic state of the system and are therefore functionally related. This approach has been termed functional redundancy or analytical redundancy. Fault detection and isolation (FDI) based on analytical redundancy techniques offer advantages in cost, weight, and reliability over the detection schemes based on redundant hardware with majority vote logic circuits.

The analytical redundancy approach for FDI in automated processes has been well discussed over the last three decades. An excellent introduction to the topic is given in [1] and [2]. Comprehensive survey papers covering the work carried out during the above period are found in [3], [4], and [5]. Different techniques for FDI in automated processes are reported in the literature such as the use of state estimators or observers, parity space approach, parameter estimation techniques and techniques based on expert systems. Recent advances in the field of FDI are described in [6] and [7].

Analytical redundancy techniques have recently been applied for fault detection and isolation in electromechanical actuators. Fault detection by parameter identification had been the approach mostly followed as demonstrated in [8], [9] [10] and [11]. Use of the Kalman filter for fault detection in a DC servo motor actuator was demonstrated by Dixon in [12]. In this work three Kalman filters were used for detecting faults in an electromechanical actuator based on a brushless motor.

This paper focuses on the detection of incipient sensor faults in a practical aerospace flight control actuation system, which is based on a DC torque motor. The analytical redundancy that exists between the linear actuator position, motor shaft angular velocity and motor current, is utilized for detection and isolation of the incipient sensor faults.

The work described in this paper is different from above mentioned approaches as only a single Kalman estimator driven by the motor shaft velocity sensor is used for FDI purpose. This makes it attractive for real time applications. The FDI approach presented in this paper has the added advantage that it permits reconfiguration of the system for fault free operation. This is demonstrated for the case of fault in the position sensor, wherein an estimate of the actuator position from the estimator is used for reconfiguration of the system for continuing the operation of the system.

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2. SYSTEM DESCRIPTION

The actuator under consideration is a linear electro mechanical actuator based on a brush type DC torque motor. The block diagram of the linear actuation system driving the load is given in Fig. 1. The linear actuator is used for actuating a rocket engine. A ball screw mechanism converts the rotary motion of the motor to linear displacement. The linear displacement of the actuator is sensed by a Linear Variable Differential Transformer (LVDT) with a scale factor of 400V/m. The system has two other sensors, a current sensor and a velocity sensor. The scale factor of the current sensor is 0.28V/A and that of the velocity sensor is 0.05V/ rad/s. The above three sensor outputs are denoted by y_{1I}, y_{2I} and y_{3I} respectively as shown in Fig. 1. The nomenclature used for describing the system is given in Table 1.

The linear state space model of the actuation system shown in Fig1 has the form

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

$$y = Cx \qquad (1)$$

$x = [x_1; x_2; x_3; x_4; x_5; x_6]$ is the system state. The parameters of A, B and C matrices are as given below.

$$\mathbf{A}=\begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ \frac{-l^2\,Ks}{J_N} & \frac{-B_N}{J_N} & \frac{N\,Ks}{J_N} & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ \frac{l^2 NKs}{J_M} & 0 & \frac{-N^2\,Ks}{J_M} & \frac{-B_M}{J_M} & \frac{K_T}{J_M} & 0 \\ 0 & 0 & 0 & \frac{-K_B}{L} & \frac{-(KiKc+R)}{L} & \frac{-Kg*Ki*(b-a)}{L} \\ 0 & 0 & 0 & 0 & 0 & -b \end{bmatrix}$$

$$\mathbf{B}= \begin{bmatrix} 0 & 0 & 0 & 0 & \frac{Kg*Ki}{L} & 1 \end{bmatrix}^{\mathbf{T}}$$

$$\mathbf{C}= \begin{bmatrix} 0 & 0 & NKp & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & Kc & 0 \\ 0 & 0 & 0 & K_V & 0 & 0 \end{bmatrix} \qquad (2)$$

Table 1: Nomenclature

Symbol	Description
B_M	Viscous damping coefficient of actuator
B_N	Viscous damping coefficient of nozzle
J_N	MI of nozzle
J_M	MI of rotating parts of torque motor with respect to motor side
K_B	Torque Motor back emf constant
K_C	Current sensor scale factor
Kv	Velocity sensor scale factor
Kg	Servo amplifier gain
K_i	Current loop forward gain
K_T	Torque constant of motor
K_S	Actuator mounting structure stiffness
K_P	LVDT Scale factor
l	Actuator lever arm length
L	Motor coil inductance
N	Ball screw gear ratio
R	Resistance of motor coil
x_1	System state – Engine Nozzle deflection
x_2	System state – Engine Nozzle deflection rate
x_3	System state - Motor shaft angle
x_4	System state - Motor shaft angular velocity
x_5	System state - Motor current
x_6	System state - Internal state of compensator
a	Compensator Zero
b	Compensator Pole
y_{1I}	Position sensor output
y_{2I}	Current sensor output
y_{3I}	Velocity sensor output

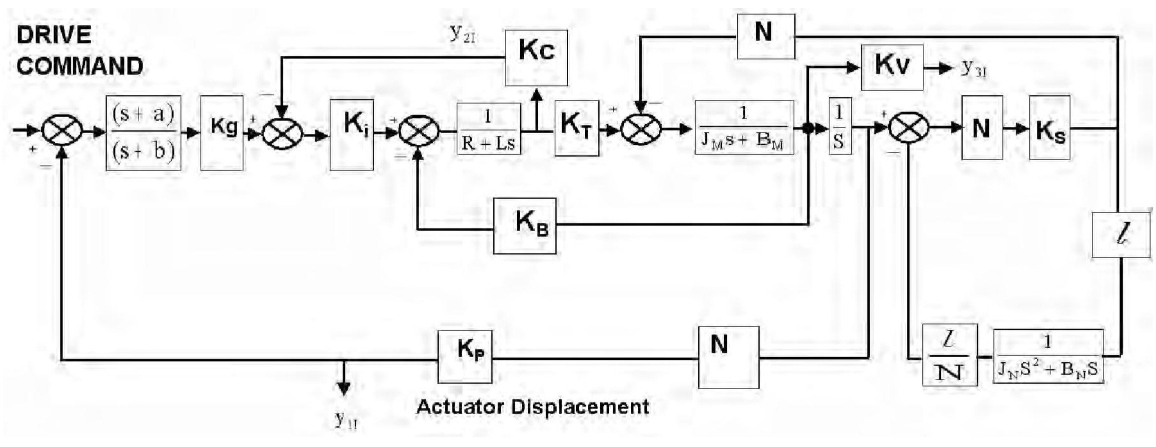

Fig 1. Block diagram of the linear actuator

3. FAULT DIAGNOSIS LOGIC

The fault diagnosis is based upon the mathematical model of the system, which is developed based on physical information and statistical data. The block diagram of the fault diagnosis scheme is shown in Fig. 2. A Kalman filter that operates from the input u and the velocity sensor output y_{3I} of the control actuation system is used for fault diagnosis purpose.

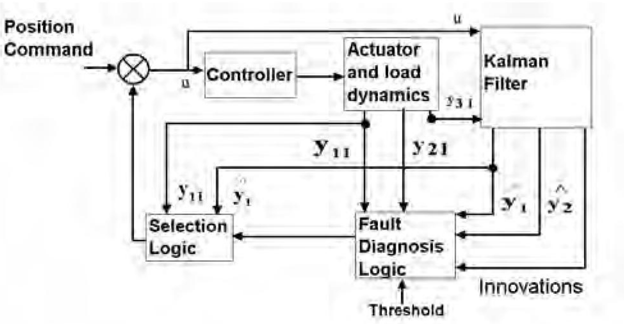

Fig. 2. Fault diagnostics scheme

3.1 The Discrete Kalman filter

For the implementation of the Kalman filter the discrete time equivalent of the system given by Eqs (1) and (2) is considered. Sampling time of 5ms is used.

$$x_{i+1} = \Phi_i x_i + G_i u_i + \Gamma_i w_i$$

$$z_i = H_i x_i + v_i, \qquad i = 0,1,2,......$$

where (3)

x_i is nx1 vector of state variables

u_i is px1 vector of control variables

w_i is qx1 vector of random forcing functions

z_i is rx1 vector of output variables

v_i is rx1 vector of random measurement errors

Φ_i is nxn state transition matrix

G_i is nxp input distribution matrix

Γ_i is nxq noise distribution matrix

H_i is rxn output matrix

The random vectors w_i and v_i are Gaussian and white. Their mean and covariance are

$$E\{w_i\} = \overline{w_i}, \qquad E\{(w_i - \overline{w_i})(w_j - \overline{w_j})^T\} = Q_i \delta_{ij}$$

$$E\{v_i\} = \overline{v_i}, \qquad E\{(v_i - \overline{v_i})(v_j - \overline{v_j})^T\} = R_i \delta_{ij}$$

$$E\{(v_i - \overline{v_i})(w_j - \overline{w_j})^T\} = 0$$

where δ_{ij} denotes the Kronecker delta

$$\delta_{ij} = \begin{cases} 1, & i = j \\ 0, & i \neq j \end{cases} \qquad (4)$$

and $E\{.\}$ denotes the expectation operator.

The initial conditions x_0 are also assumed to be random. Their distribution is Gaussian with mean and covariance

$$E\{x_0\} = \overline{x_0}, \quad E\{(x_0 - \overline{x_0})(x_0 - \overline{x_0})^T\} = P_0$$

The innovation sequence γ_i is defined as

$\gamma_i = z_i - \hat{z}_{i/i-1}$ where $\hat{z}_{i/i-1}$ denotes the unbiased minimum variance estimate of z_i based on observations up to (i-1). The innovation sequence can be generated by a Kalman filter of the following form

$$\hat{x}_{i+1/i} = \Phi[\hat{x}_{i/i-1} + K_i \gamma_i] + G_i u_i + \Gamma_i w_i$$

$$\gamma_i = z_i - H_i \hat{x}_{i/i-1}$$

$$K_i = P_{i/i-1} H_i^T (H_i P_{i/i-1} H_i^T + R_i)^{-1}$$

$$P_{i+1/i} = \Phi_i P \Phi_i^T + \Gamma_i Q_i \Gamma_i^T$$

$$P_{i/i} = (I - K_i H_i) P_{i/i-1}$$

(5)

where $\hat{x}_{i/j}$ is the unbiased minimum variance estimate of x_i based on observations up to time j.

K_i is n x r Kalman gain matrix and $P_{i/j}$ is the error covariance of $\hat{x}_{i/j}$

i.e. $P_{i/j} = E\{(x_i - \hat{x}_{i/j})(x_i - \hat{x}_{i/j})^T\}$

3.2 Fault detection using the innovation sequence

For unique fault isolation capability *structured* residuals are formed from the Kalman filter that operates from the input u and the velocity sensor output y_{3I} of the control actuation system. For this purpose, it is first essential to establish that the velocity sensor driving the Kalman filter itself is not faulty. This is done using the innovation sequence of the Kalman filter. When the system is working in the fault free condition the innovation sequence has the property that it is a zero mean Gaussian white noise process with covariance

$$(H_i P_{i/i-1} H_i^T + R_i)$$

Different kind of faults such as bias in sensors, scale factor errors, etc can develop in a system. All of these faults make the innovation sequence γ_i of the Kalman filter depart from their zero mean, unit variance and whiteness properties. Therefore faults in the system can be detected by performing certain statistical tests on the innovation sequence of the Kalman filter.

The problem of fault detection is formulated as a problem in hypothesis testing by regarding the normal operation of the system as a null hypothesis. The innovation sequence is tested against this hypothesis at a certain level of significance. For Hypothesis testing purpose the normalized innovation sequence is considered

$$\eta_i = (H_i P_{i/i-1} H_i^T + R_i)^{\frac{-1}{2}} \gamma_i \qquad (6)$$

where $(.)^{\frac{-1}{2}}$ denotes the square root of the inverse of a matrix.

In this work the innovation sequence is tested for the property of zero mean. The mean of the innovation sequence is estimated as

$$\bar{\eta} = \frac{1}{N}\sum_{i=1}^{N}\eta_i \tag{7}$$

where N is the sample size and $\bar{\eta}$ denotes the true mean. Under the null hypothesis, $\bar{\eta}$ has a Gaussian distribution with zero mean.

3.3 Fault diagnosis using structured residuals

The FDI algorithm initially checks for the zero mean property of the innovation sequence and confirm that the velocity sensor is working properly. If there is no fault in the velocity sensor the algorithm proceeds and checks for faults in the position and current sensors. This is carried out using the *structured* residuals generated from the Kalman filter estimates.

In the absence of disturbances and plant uncertainty, if all the sensors are working perfectly, the estimated sensor outputs generated by the Kalman estimator are

$$\hat{y} = \begin{bmatrix} \hat{y}_1; & \hat{y}_2; & \hat{y}_3 \end{bmatrix} \tag{8}$$

where $\hat{y}_1, \hat{y}_2$ and $\hat{y}_3$ are the estimates of actuator position, motor current, and motor shaft velocity. Under fault free conditions this will match the actual sensor outputs of actuator position, motor current and motor shaft velocity (y_{1I}, y_{2I} and y_{3I}). The following *structured* residuals are formed for fault diagnosis.

$$R1 = \Delta y_1 = y_{1I} - \hat{y}_1$$

$$R2 = \Delta y_2 = y_{2I} - \hat{y}_2 \tag{9}$$

In the absence of faults the magnitude of the residuals will be near zero, as the estimated outputs will match the true sensor outputs. A fault in position sensor causes an increase in R1 while R2 will remain near zero. Similarly a fault in current sensor causes an increase in R2 while R1 will remain near zero. Thus by checking the magnitude of residuals R1 and R2 fault diagnosis in the position and current sensor can be achieved.

Even in the absence of faults in any of the three sensors the magnitude of the residuals need not be exactly zero due to the presence of noise in the instruments and also due to errors in the estimator design parameters. Hence, to avoid false alarms, a threshold level of magnitude 0.5 was selected for residuals R1 and R2 for declaring a fault.

4. SIMULATION RESULTS

Simulation studies were carried out on the formulated FDI scheme to assess its efficiency in detecting faults in the sensors. Substituting the values of the various system parameters the state transition matrix Φ_i and input distribution matrix G_i are obtained as follows.

$$\Phi = \begin{bmatrix} 0.8789 & 0.00474 & 0.0009691 & 1.621\,E-6 & 1.109\,E-7 & -0.001675 \\ -46.97 & 0.857 & 0.3759 & 0.000957 & 6.709E-5 & -1.285 \\ 4.078 & 0.006852 & 0.9674 & 0.004851 & 0.0003481 & -9.098 \\ 1577 & 4.046 & -12.62 & 0.9295 & 0.06848 & -3043 \\ -17.9 & -0.04479 & 0.1433 & -0.01081 & -0.0007965 & -501.1 \\ 0 & 0 & 0 & 0 & 0 & 0.2753 \end{bmatrix}$$

$$G = [8.223\ E-6; \quad 0.006389 \quad 0.04617 \quad 16.21 \quad 3.437 \quad 0.002809]$$

$$H = [0 \quad 0 \quad 0 \quad 0.05 \quad 0 \quad 0]$$

The initial value of the states are assumed to be zero with covariance

$$P_0 = \mathrm{diag}[0.0003; \quad 0.0003; \quad 0.0003; \quad 0.0003; \quad 0.01; \quad 0.01]$$

The process noise is assumed to be zero. Zero mean white Gaussian noise corresponding to 0.1mm, 1 rad/s and 0.1 A is added to the position, velocity and current sensor respectively. The sensor noise covariance R for the kalman filter is taken as R=[0.0025]

The command given to the system consists of a pulse train of amplitude corresponding to 2.5mm movement of the actuator. The period of the pulse is 2 second with 50% duty cycle. As the emphasis here is on detecting incipient faults, bias faults and scale factor faults were introduced in the sensors during the simulations. The faults are introduced in the sensors from 2 second onwards. Fig. 3 and Fig. 4 shows the estimated output of the position and current from the estimator when there is no fault in the system.

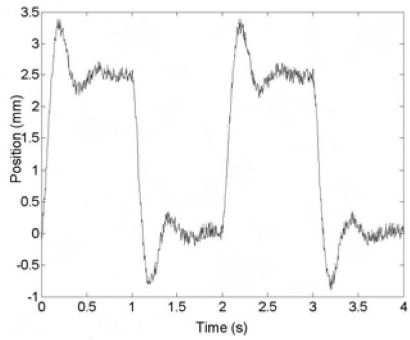

Fig 3: Estimated position

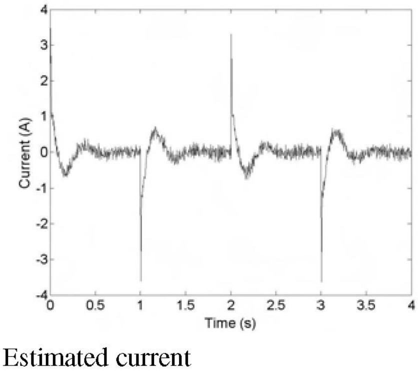

Fig 4: Estimated current

These estimated outputs are used along with the actual outputs sensed by the instruments y_{1I}, and y_{2I} for generating the residuals.

4.1 Fault detection in the velocity sensor

The FDI algorithm initially checks the normalized innovation sequence for zero mean to confirm that the velocity sensor driving the Kalman filter is functioning normally. The sample size used for computing the mean is N=10. After confirming that the velocity sensor is functioning normally, the algorithm checks the magnitude of residuals R1 and R2 for detecting faults in the position and current sensor.

The mean of the innovation sequence when the system is working normally is shown in Fig 5.

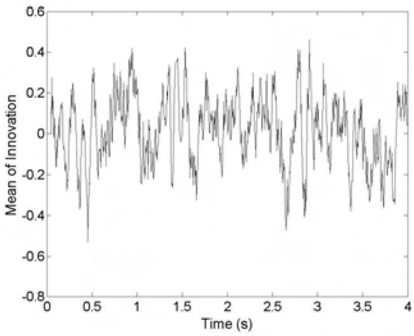

Fig 5: Mean of the innovation in normal condition

The maximum magnitude of the mean of the innovation sequence in the fault free condition is 0.5. To avoid false alarms a threshold level of 3 was selected for the innovation mean for declaring a fault. Fig 6 shows the case when a scale factor fault of 25% is present in the velocity sensor. Fig 7 shows the case when a bias error of 5 rad/s is present in the velocity sensor. In both these cases it is found that the fault is detected as the magnitude of the innovation crosses the threshold value.

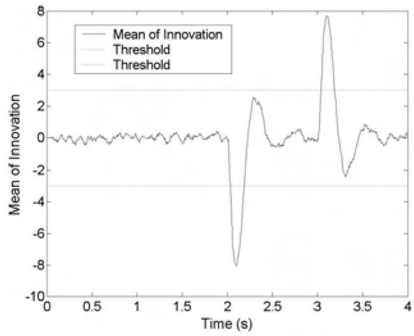

Fig 6: Scale factor fault of 25% in velocity sensor

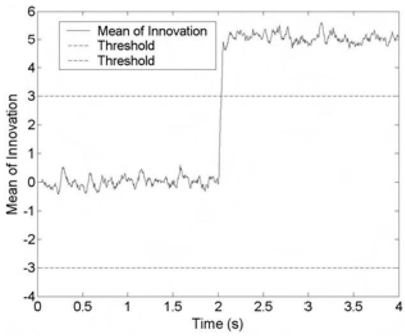

Fig 7: Bias fault of 5 rad/s in velocity sensor

4.2 Fault detection in the position sensor

The magnitude of the residuals for a 25% scale factor fault in the position sensor is shown in Fig 8. Fig 9 shows the case of bias fault of 1 mm in the position sensor. In these cases it is clearly seen that the magnitude of the residual R1 crosses the threshold level signaling that the position sensor is faulty. The magnitude of residual R2 remains near zero indicating the normal functioning of the current sensor.

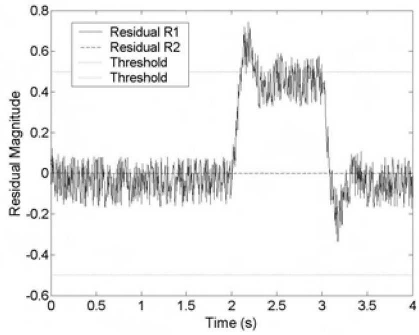

Fig 8: Scale factor fault of 25% in position sensor

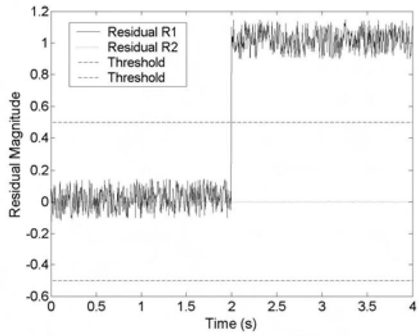

Fig 9: Bias fault of 1 mm in position sensor

4.3 Fault detection in the current sensor

The magnitude of the residuals for a 25% fault in the current sensor is shown in Fig 10. Fig 11 shows the magnitude of the residuals for a bias fault of 1 A in the current sensor. It is seen that the magnitude of the residual R2 crosses the threshold level of 0.5 indicating that the current sensor is faulty.

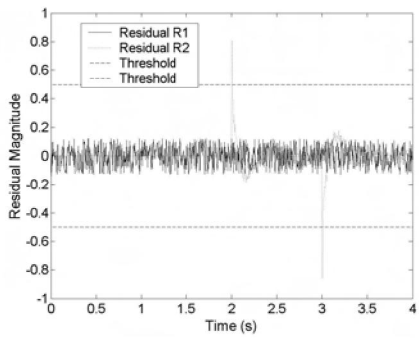

Fig 10: Scale factor fault of 25% in current sensor

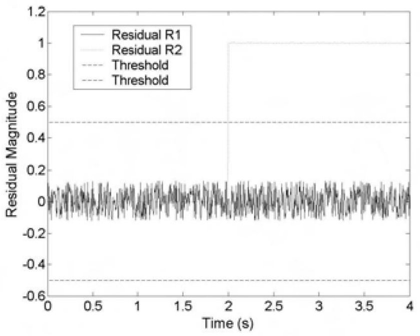

Fig 11: Bias fault of 1 A in current sensor

4.4 Robustness to parameter variations

For assessing the robustness of the FDI scheme the resistance of the motor coil was changed by 5% during simulations. The maximum value of the mean of the innovation sequence under this condition is found to be 1, which is less than the threshold value of 3. Thus no false alarm will be generated under this condition. The magnitude of the residuals R1 and R2 under this condition is 0.2 and 0.1 respectively, which is again less that the threshold level of 0.5.

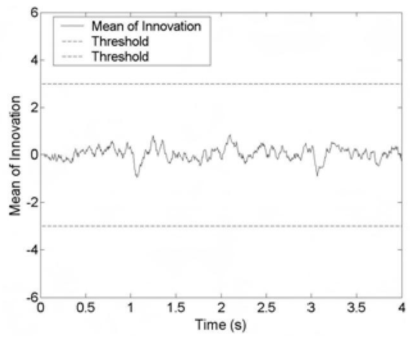

Fig 12: 5% variation in motor coil resistance

4.5 Reconfiguration on position sensor fault

In this FDI scheme reconfiguration of control in the event of a failure in the position sensor is possible. For reconfiguration, the position sensor output as well as the estimated position from the Kalman filter is routed through selection logic as shown in Fig 2. On detecting a fault from the position sensor the actuator loop is closed using the position output of the estimator. Fig 13 shows the case of reconfiguration of the control system on detection of a 25% scale factor fault in the position sensor.

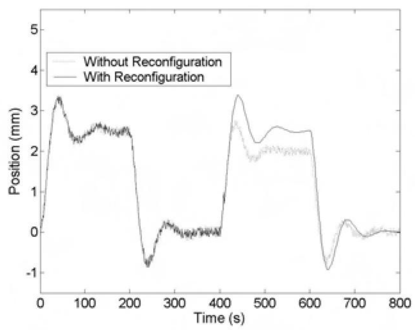

Fig13: Reconfiguration on position sensor fault

It is seen that in the absence of any reconfiguration the actuator settles to about 2 mm instead of the commanded value of 2.5 mm. It is observed from Fig 13 that after reconfiguration the system settles to the commanded value of 2.5mm and continues to operate smoothly.

5. CONCLUSION

A scheme for detection of incipient sensor faults in a flight control actuation system is presented. The FDI scheme presented is attractive for real time implementation in flight control actuation systems as only a single estimator is required for fault diagnosis.
The efficiency of the scheme to detect incipient faults in the sensors such as bias faults and scale factor faults is demonstrated. Robustness of the scheme to parameter variations is examined. Reconfiguration of control in the event of fault in the position sensor is carried out using the estimate of position provided by the kalman filter. The results obtained are encouraging for pursuing further work in this area. Design of unknown input observers that are more robust to unknown inputs like system disturbances can be pursued. This shall be the focus of future work.

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