Preprints of the 19th World Congress
The International Federation of Automatic Control
Cape Town, South Africa. August 24-29, 2014

Sensor and Actuator FDI Applied to an UAV Dynamic Model

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Abstract: In this paper, an approach to isolate the sensor and control surface/actuator failures affecting the innovation of Kalman filter was proposed and applied to an UAV dynamic model. To diagnose if the fault is a sensor fault or an actuator fault, a two-stage Kalman filter (TSKF) insensitive to actuator faults is developed. In the proposed method, sensor faults are isolated by the normalized innovation of Kalman filter. Furthermore, an adaptive linear adaptive TSKF algorithm is used to estimate the loss of control effectiveness and the magnitude of degree of stuck faults in a UAV model. Control effectiveness factors and stuck magnitudes are used to quantify faults entering control systems through actuators. In the simulations, the longitudinal and lateral dynamics of the UAV model is considered, and detection and isolation of sensor and control surface/actuator failures are examined.

Keywords: Fault Detection, Fault Isolation, Fault Identification, Kalman Filter, Innovation sequence, Two Stage Adaptive Kalman filter, UAV dynamics.

1. INTRODUCTION

Many fault detection filters have been developed to detect and identify sensor and actuator faults by using analytical redundancy. Larson et al. (2002) developed an analytical redundancy-based approach for detecting and isolating sensor, actuator, and component (i.e., plant) faults in complex dynamical systems, such as aircraft and spacecraft. A statistical change detection technique based on a modification of the standard generalized likelihood ratio (GLR) statistic is used to detect faults in real time. The GLR test requires the statistical characteristics of the system to be known before and after the fault occurs.

Maybeck (1999) incorporated multiple model adaptive estimation (MMAE) methods into the design of a flight control system for the variable in-flight stability test aircraft (VISTA) F-16, providing it with the capability to detect and compensate for sensor and control surface/actuator failures. The algorithm consists of a `front end' estimator for the control system, composed of a bank of parallel Kalman filters, each matched to a specific hypothesis about the failure status of the system (fully functional or a failure in any one sensor or surface/actuator), and a means of blending the filter outputs through a probability-weighted average.

One of the diagnosis approaches based on Kalman filtering is the analysis of the innovation sequence. These approaches do not require a priori statistical characteristics of the faults, and the computational burden is not very heavy. If the system operates normally, the normalized innovation sequence in a Kalman filter is a Gaussian white noise with a zero mean and with a unit covariance matrix. Faults that change the system dynamics by causing surges of drifts of the state vector components, abnormal measurements, sudden shifts in the measurement channel, and other difficulties such as decrease of instrument accuracy, an increase of background noise, reduction in control surface/actuator effectiveness etc., effect the characteristics of the normalized innovation sequence by changing its white noise nature, displacing its zero mean, and varying unit covariance matrix. Methods of testing the agreement between the innovation sequence and white noise, and the detection of any change of its mathematical expectation are discussed, and the approaches that verify the covariance matrix of the innovation process are addressed in the monograph by Hajiyev and Caliskan (2003).

Boskovic and Mehra (2001) presented a Failure Detection and Identification (FDI) and Adaptive Reconfigurable Control (ARC) scheme for accommodation of control effector failures such as lock-in-place and hard-over. The overall system consisting of on-line FDI observers for all control effectors guarantees asymptotic tracking, and ensures convergence of the failure-related parameter estimate to its true value. The scheme can identify rapidly and accurately different control effector failures like float, hard-over, lock-in-place and loss of effectiveness. They used adaptive interacting multiple observers to estimate the actuator faults and tested the scheme on a linearized model of the Boeing's tailless advanced fighter aircraft.

The two-stage Kalman filter of Keller and Darouach (1997) was applied to estimating simultaneously the state and the control effectiveness of a linear aircraft model in Wu, Zhang, and Zhou (2000). Thus the filter acquired the name adaptive two-stage Kalman filter (TSKF). The state and control effectiveness estimates with the adaptive TSKF approach have been utilized to help achieve fault-tolerant control of impaired linear aircraft model in a number of papers by the authors (Zhang and Jiang, 2002; and Shin, Wu, and Belcastro, 2004, for example).

Caliskan et al. (2009) used a linear adaptive TSKF algorithm (Wu, Zhang, and Zhou, 2000) to estimate the loss of control effectiveness and the magnitude of low degree of stuck faults in a closed-loop nonlinear B747 aircraft. Control effectiveness factors and stuck magnitudes are used to quantify faults entering control systems through actuators. Pseudo random excitation inputs are used to help distinguish partial loss and stuck faults. The partial loss and stuck faults in the stabilizer are identified successfully.

Amoozgar et al. (2013) addressed the problem of Fault Detection and Diagnosis (FDD) of a quadrotor helicopter system in the presence of actuator faults. TSKF is used to simultaneously estimate and isolate possible faults in each actuator. The faults are modelled as losses in control effectiveness of rotors.

Yang et al. (2013) presented a recursive strategy for online detection of actuator faults on a unmanned aerial system (UAS) subjected to accidental actuator faults. The proposed detection algorithm aims to provide a UAS with the capability of identifying and determining characteristics of actuator faults, offering necessary flight information for the design of fault-tolerant mechanism to compensate for the resultant side-effect when faults occur. The proposed fault detection strategy consists of a bank of unscented Kalman filters (UKFs) with each one detecting a specific type of actuator faults and estimating corresponding velocity and attitude information. Performance of the proposed method is evaluated using a typical nonlinear UAS model and it is demonstrated in simulations that our method is able to detect representative faults with a sufficient accuracy and acceptable time delay, and can be applied to the design of fault-tolerant flight control systems of UASs.

In this study, an effective approach to isolate the sensor and control surface/actuator failures affecting the innovation of Kalman filter is proposed and applied to an UAV dynamic model. This paper generalizes the design model for the linear adaptive TSKF of Wu, Zhang, and Zhou (2000) to include stuck faults in control surfaces. The approach is applied to state and parameter estimation for a UAV model. Our findings indicate that the adaptive TSKF can correctly estimate the UAV states, as well as the actuator parameters. Fault parameterization in the design model of the linear estimator aims to capture the degree at which a control surface is stuck, and the extent at which the control effectiveness is lost. The estimates serve to support real-time assessment of post-failure flight envelope.

2. MATHEMATICAL MODEL OF THE UAV DYNAMICS

The dynamic characteristic of an aircraft must be known in order to build a Kalman filter for the state estimation. In general, equation derivation process for an aircraft may be examined in two steps; derivation of the rigid body equations of motion and the linearization (Yechout et al. 2003).

In general, the equations are considered in two phases; longitudinal and lateral. These nonlinear equations can be linearized by using the small perturbation theory. Hereafter, the term $\Delta(.)$ is used for representing the perturbed state.

Consequently, the linearized longitudinal equations of motion of UAV in the state space form is,

$$x_{k+1}^{lon} = A^{lon} x_k^{lon} + B^{lon} u_k^{lon}$$

$$\begin{bmatrix} \Delta\dot{u} \\ \Delta\dot{w} \\ \Delta\dot{q} \\ \Delta\dot{\theta} \\ \Delta\dot{h} \end{bmatrix} = \begin{bmatrix} X_u & X_w & 0 & -g & 0 \\ Z_u & Z_w & u_0 & 0 & 0 \\ M_u + M_{\dot{w}} Z_u & M_w + M_{\dot{w}} Z_w & M_q + M_{\dot{w}} u_0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & -1 & 0 & u_0 & 0 \end{bmatrix} \begin{bmatrix} \Delta u \\ \Delta w \\ \Delta q \\ \Delta\theta \\ \Delta h \end{bmatrix}$$

$$+ \begin{bmatrix} X_{\delta e} & X_{\delta T} \\ Z_{\delta e} & Z_{\delta T} \\ M_{\delta e} + M_{\dot{w}} Z_{\delta e} & M_{\delta T} + M_{\dot{w}} Z_{\delta T} \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \Delta\delta_e \\ \Delta\delta_T \end{bmatrix} \tag{1}$$

and the linearized lateral equations of motion of UAV in the state space form is,

$$x_{k+1}^{lat} = A^{lat} x_k^{lat} + B^{lat} u_k^{lat}$$

$$\begin{bmatrix} \Delta\dot{\beta} \\ \Delta\dot{p} \\ \Delta\dot{r} \\ \Delta\dot{\phi} \end{bmatrix} = \begin{bmatrix} \frac{Y_\beta}{u_0} & \frac{Y_p}{u_0} & -\frac{u_0 - Y_r}{u_0} & \frac{g\cos(\theta_0)}{u_0} \\ L_\beta & L_p & L_r & 0 \\ N_\beta & N_p & N_r & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} \Delta\beta \\ \Delta p \\ \Delta r \\ \Delta\phi \end{bmatrix} + \begin{bmatrix} 0 & \frac{Y_{\delta r}}{u_0} \\ L_{\delta a} & L_{\delta r} \\ N_{\delta a} & N_{\delta r} \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \Delta\delta_a \\ \Delta\delta_r \end{bmatrix} \tag{2}$$

where, Δu, Δw are the velocity components $\Delta p, \Delta q, \Delta r$ are the angular rates, $\Delta\delta_e$, $\Delta\delta_a$ and $\Delta\delta_r$ are the elevator, aileron and the rudder deflections, $\Delta\delta_T$ is the change in the thrust, $\Delta\theta$ is the pitch angle about y axis, $\Delta\phi$ is the roll angle about x axis, $\Delta\beta$ is the sideslip angle, Δh is the height, θ_0 and u_0 are the values of related terms in the steady state flight, g is the gravity constant and X_u, X_w, $X_{\delta e}$, $X_{\delta T}$, Z_u, Z_w, $Z_{\delta e}$, $Z_{\delta T}$, M_u, M_w, M_q, $M_{\dot{w}}$, Y_r, Y_p, Y_β, $Y_{\delta r}$, L_β, L_p, L_r, $L_{\delta a}$, $L_{\delta r}$, $M_{\delta e}$, $M_{\delta T}$, $N_{\delta a}$, $N_{\delta r}$, N_β, N_p, N_r are the stability derivatives. Integrating the longitudinal and lateral equations of UAV results in the equations as (Hajiyev and Soken, 2012)

$$\begin{aligned} x_{k+1} &= Ax_k + Bu_k + w_k^x \\ y_{k+1} &= Cx_{k+1} + v_{k+1} \end{aligned} \tag{3}$$

where

$$x_k = [\Delta u \quad \Delta w \quad \Delta q \quad \Delta\theta \quad \Delta h \quad \Delta\beta \quad \Delta p \quad \Delta r \quad \Delta\phi]_k^T ,$$

$$u_k = [\Delta\delta_e \quad \Delta\delta_T \quad \Delta\delta_a \quad \Delta\delta_r]_k^T$$

$$A = \begin{bmatrix} A^{lon} & 0 \\ 0 & A^{lat} \end{bmatrix}, B = \begin{bmatrix} B^{lon} & 0 \\ 0 & B^{lat} \end{bmatrix}$$

3. SENSOR FAULT DETECTION AND ISOLATION

3.1. The Statistical Test for Fault Detection

Two hypotheses are introduced:

H_0 *: System operates normally,*

H_1 *: Fault occurs in the system.*

Using innovation approach is suitable for detecting sensor faults (Hajiyev and Caliskan, 2003). To detect failures changing the mean of the innovation sequence the following statistical function can be used

$$\beta_k = \sum_{j=k-M+1}^{k} \tilde{\Delta}_j^T \tilde{\Delta}_j \tag{4}$$

where $\tilde{\Delta}_j$ is the normalized innovation sequence of the Kalman filter, M is the width of the sliding window.

The Kalman filter normalized innovation can be calculated as follows:

$$\tilde{\Delta}_k = [C_k P_{k/k-1} C_k^T + R_k]^{-1/2} (y_k - C_k \hat{x}_{k/k-1}) \tag{5}$$

where $\hat{x}_{k/k-1}$ is the prediction in one step, $P_{k/k-1}$ is the prediction covariance, R_k is the covariance of measurement noise .

This statistical function has χ^2 distribution with M.s degree of freedom, where s is the dimension of the state vector. If the level of significance, α , is selected as,

$$P\{\chi^2 > \chi^2_{\alpha,Ms}\} = \alpha \; ; \qquad 0 < \alpha < 1 \tag{6}$$

the threshold value, $\chi^2_{\alpha,Ms}$ can be found. Hence, when the hypothesis H_1 is true, the statistical value of β_k will be greater than the threshold value $\chi^2_{\alpha,Ms}$, i.e.:

$$\begin{aligned} H_0 &: \beta_k \le \chi^2_{\alpha,Ms}, \forall k \\ H_1 &: \beta_k > \chi^2_{\alpha,Ms}, \exists k \end{aligned} \tag{7}$$

3.2. Sensor Fault Isolation Algorithm

If the fault is detected, then it is necessary to determine what sensor set is faulty. For this purpose, the s-dimensional sequence $\tilde{\Delta}$ is transformed into s one-dimensional sequences to isolate the faulty sensor, and for each one-dimensional sequence $\tilde{\Delta}_i (i = 1,2,..., s)$ corresponding monitoring algorithm is run. The statistics of the faulty sensor set is assumed to be affected much more than those of the other sensors. Let the statistics is denoted as $S_i(k)$. When $\max\{S_i(k) / i = 1,2,...,s\} = S_m(k)$ for $i \neq j$, and $S_i(k) \neq S_j(k)$, it is judged that sensor set has failed.

Let the statistics which is a rate of sample and theoretical variances; $\hat{\sigma}_i^2 / \sigma_i^2$ be used to verify the variances of one dimensional innovation sequences $\tilde{\Delta}_i(k), i = 1,2,..., s$. When $\tilde{\Delta}_i \sim N(0, \sigma_i)$ it is known that (Hajiyev and Caliskan, 2005)

$$\frac{\nu_i}{\sigma_i^2} \sim \chi^2_{M-1}, \forall i, i = 1,2,\ldots,s \tag{8}$$

where $\nu_i = (M-1)\hat{\sigma}_i^2$. As $\sigma_i^2 = 1$ for normalized innovation sequence it follows that,

$$\nu_i \sim \chi^2_{M-1}, \forall i, i = 1,2,\ldots,s \; . \tag{9}$$

Using (9) it can be proved that any change in the mean of the normalized innovation sequence can be detected. When a fault affecting the mean or variance of the innovation sequence, occurs in the system the statistics ν_i exceeds the threshold value $\chi^2_{\alpha,M-1}$ depending on the level of significance α , and degree of freedom M-1. The decision making for isolation is done as follows; if the hypothesis H_1 is true and $\nu_i(k) \neq \nu_j(k), i \neq j$ and $\max\{\nu_i(k) / i = 1,2,...,s\} = \nu_m(k)$, then it is judged that there is a fault in the m^{th} channel.

4. ADAPTIVE TSKF ALGORITHM FOR STATE ESTIMATION AND ACTUATOR FAULT IDENTIFICATION

Based on the linearized model of the open-loop UAV around a trim point, and a parameterization of two types of actuator faults, the following discrete time model is used as the design model of the adaptive TSKF

$$\begin{aligned} x_{k+1} &= A_k x_k + B_k u_k + E_k \gamma_k + B_k \beta_k + w_k^x \\ \zeta_{k+1} &= \zeta_k + w_k^\zeta, \quad \zeta_k = [\gamma_k^T \quad \beta_k^T]^T \\ y_{k+1} &= C_{k+1} x_{k+1} + v_{k+1} \end{aligned} \tag{10}$$

where $x_k \in R^n, u_k \in R^l$ and $y_{k+1} \in R^s$ are the state, control input and output variables, respectively. γ_k and β_k are bias vectors of dimension *l*, representing faults entering actuators. The noise sequences w^x, w^ζ and v are assumed to be zero mean uncorrelated white Gaussian noise sequences with

$$E\left\{ \begin{bmatrix} w_k^x \\ w_k^\zeta \\ v_k \end{bmatrix} \begin{bmatrix} w_j^x & w_j^\zeta & v_j \end{bmatrix} \right\} = \begin{bmatrix} Q^x & 0 & 0 \\ 0 & Q^\zeta & 0 \\ 0 & 0 & R \end{bmatrix} \delta_{kj} \tag{11}$$

where $Q^x > 0, Q^\zeta > 0, R > 0$ and δ_{kj} is the Kronecker delta. The initial states $x(0)$ and $\zeta(0)$ are assumed to be uncorrelated with the white noise processes w^x, w^ζ and v, and have covariances $\tilde{P}_0^x$ and $\tilde{P}_0^\zeta$, respectively. The components

$$-1 \leq \gamma_k^i \leq 0, j = 1,2,\cdots,l \tag{12}$$

of bias vector γ_k describe percent reduction in control effectiveness when the terms $B_k u_k + E_k \gamma_k$ are considered together, where

$$E_k = B_k U_k \text{ and } U_k = diag\,(u_k^1 \ldots u_k^l)\,. \tag{13}$$

Estimator design model (10) is inherited from Equation (12) of Wu, Zhang, and Zhou (2000), with a set of new bias components

$$\beta_k^i, i = 1,\ldots,l \tag{14}$$

added in this paper to denote the degrees at which control surfaces are stuck. A stuck fault is modelled by the combination of the following three terms (10)

$$B_k u_k + E_k \gamma_k + B_k \beta_k\,. \tag{15}$$

We now summarize the cases the fault parameter values represented. Specifically, no-fault case is represented by

$$\gamma_k^i = 0 \text{ and } \beta_k^i = 0 \quad i=1, 2,\ldots, l; \tag{16}$$

$100\gamma_k^i\%$ loss of control effectiveness in the *i*-th actuator is represented by

$$-1 \leq \gamma_k^i \leq 0 \text{ and } \beta_k^i = 0\,; \tag{17}$$

control surface stuck at magnitude β_k^i degrees is represented by

$$\gamma_k^i = -1 \text{ and } \beta_k^i \neq 0\,. \tag{18}$$

The linear adaptive TSKF of Wu *et al*. (2000) can be directly applied to estimate both γ_k and β_k via generalizing $E_k\gamma_k$ to

$$\begin{aligned} &E_k\gamma_k + B_k\beta_k = [E_k \quad B_k]\,[\gamma_k^T \quad \beta_k^T]^T = [E_k \quad B_k]\,\zeta_k; \\ &\text{where } \zeta_k = \left[\gamma_k^T \quad \beta_k^T\right]^T \end{aligned} \tag{19}$$

which model the stuck fault as well, in addition to the loss of control effectiveness fault originally considered in Wu *et al.* (2000). Since $E_k = B_k U_k$,

$$E_k\gamma_k + B_k\beta_k = B_k U_k \gamma_k + B_k\beta_k = B_k\left[U_k\gamma_k + \beta_k\right] \tag{20}$$

Therefore, the entries of $U_k = diag\,(u_k^1 \ldots u_k^l)$ must vary and evolve in time independently (persistently excited) to allow the estimator to distinguish between γ_k and β_k and among their components.

5. SENSOR/ACTUATOR FDI METHOD

Detection and isolation of both sensor and actuator faults is considered for the UAV model. The sensor fault is represented by the difference between real and estimated values of measured output. The proposed fault detection and isolation method works with the assumption that only one sensor or one actuator is faulty at a time, which is a reasonable assumption in practice. To detect failures affecting the innovation sequence the statistical function (4) and the decision making rule (7) can be used. In TSKF, the loss of control effectiveness factor γ and control surface stuck factor β are estimated. If no fault has occurred, $\hat{\gamma}$ and $\hat{\beta}$ will remain zero. If the system is faulty, then $\hat{\gamma}$ or $\hat{\beta}$ derived from TSKF is nonzero. To diagnose if the fault is a sensor fault or an actuator fault, a squared residual e is introduced as follows

$$e_k = (y_k - C_k x_{est_k})^T (y_k - C_k x_{est_k}) \tag{21}$$

where x_{est_k} is the estimated state of the TSKF. If an actuator fault occurs, the mean value of the residual e_k should be close to zero (limited between zero and a threshold value). Otherwise, the mean value of e_k will exceed the threshold and the sensor fault will be determined. In the proposed method, sensor faults are isolated by the Kalman filter normalized innovation using (9). The actuator faults are isolated and identified through the TSKF above.

6. SIMULATION RESULTS

6.1 Simulation results for sensor actuator fault isolation

A pitch rate gyro fault is assumed to occur at t=20s. The fault in the pitch rate gyro is simulated by adding the constant bias 0.01rad/s. By means of the TSKF, the squared error between the actual states and the estimated states are defined as (21), and plotted as in Fig.1.

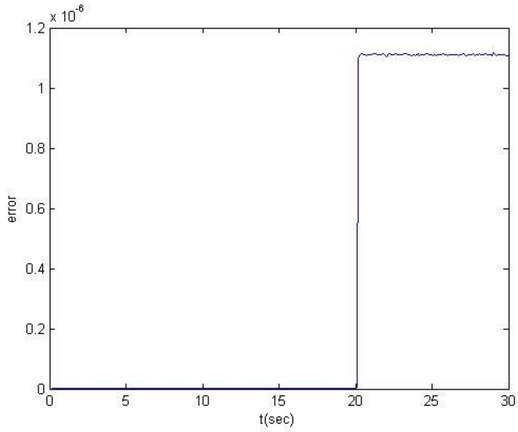

Fig.1. Squared residual between the actual states and the estimated states in the case of pitch rate gyro fault

As the TSKF is not sensitive to actuator faults but sensitive to sensor faults, the jump in the graph at t=20s reveals a sensor fault (the residual exceeds the selected threshold value 0.4×10^{-6}).

6.2 Simulation results for sensor fault isolation

A Kalman filter is used to detect and isolate the sensor faults. The combined longitudinal and lateral dynamics for UAV state estimation, the augmented state and control vectors are as in (3). When a fault in the pitch rate gyro has occurred, only S3 component exceeds the threshold as shown in Fig 2.

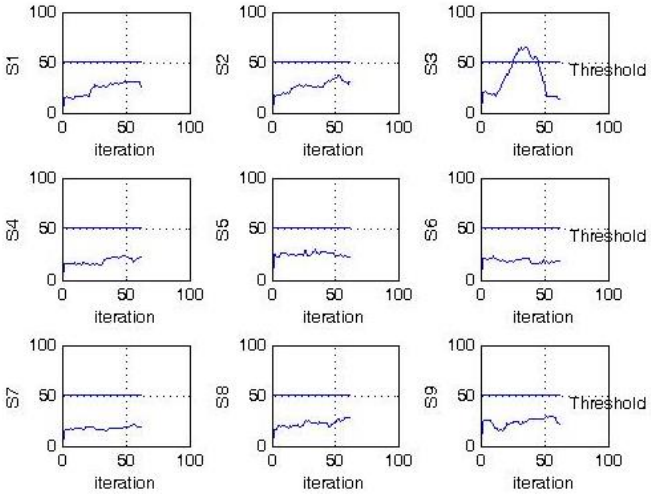

Fig. 2 Fault isolation in the pitch rate gyro

6.3 Simulation results for actuator fault isolation and identification

Throughout the simulations the symbols seen in the figures are as follows: the surface fault parameter vector is $[\zeta^1\ \zeta^2\ \zeta^3\ \zeta^4\ \zeta^5\ \zeta^6 \zeta^7\ \zeta^8]^T = [\gamma^1\ \gamma^2\ \gamma^3 \gamma^4\ \beta^1\ \beta^2\ \beta^3 \beta^4]^T$. The actuator faults are assumed to occur symmetrically, i.e. right and left elevators are considered to move together.

Experiment 1: Stuck fault in the elevator at 0.05 (rad) at 20 seconds.

As the TSKF is not sensitive to actuator stuck fault, there is no jump at t=20s in the graph in contrast to sensor faults as seen in Fig.3. The error is very small.

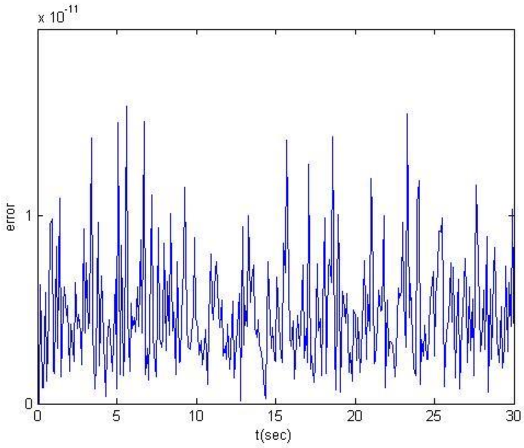

Fig.3. Squared residual between the actual states and the estimated states in the case of stuck actuator fault

Under the fault condition, simulation results for stuck fault estimation are shown in Fig. 4. The states are estimated correctly before and after occurrence of the stuck fault in the elevator.

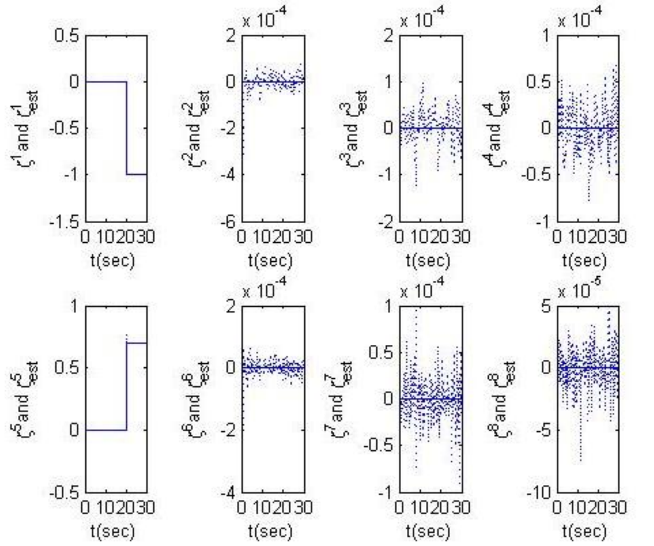

Fig.4. Actual inputs and estimations when a stuck actuator fault in the elevator occurred at 20 seconds.

From Fig. 4, it can be concluded that a stuck actuator fault with magnitude 0.05 (rad) has occurred in the elevator because $\hat{\zeta}^1 = \hat{\gamma}^1 = -1$ and $\hat{\zeta}^5 = \hat{\beta}^1 = 0.7$. When $\hat{\gamma}$ becomes -1, we can obtain the estimated stuck magnitude in the corresponding control channel.

Experiment 2: 50% partial loss in the elevator at 20 seconds.

As the TSKF is not sensitive to actuator partial loss either, there is no jump at t=20s. in the graph in contrast to sensor faults as seen in Fig.5. The error is very small. The states are estimated correctly before and after occurrence of the partial loss in the elevator.

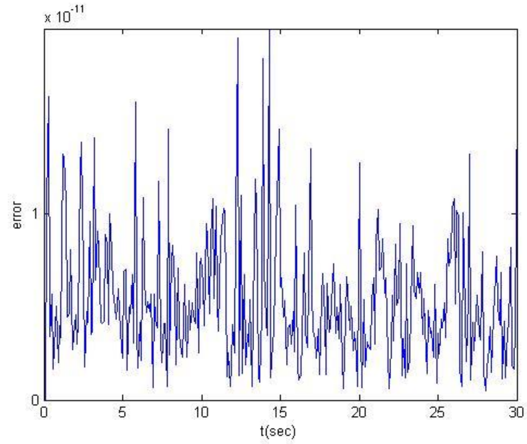

Fig.5. Squared residual between the actual states and the estimated states in the case of actuator loss of effectiveness

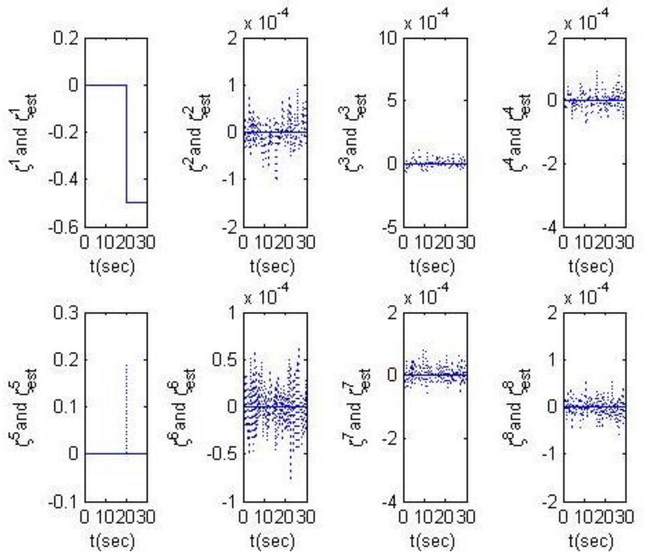

Fig. 6 Actual inputs and estimations when 50% partial loss in the elevator occurred at 20 seconds.

In Fig. 6, $\hat{\zeta}^1 = \hat{\gamma}^1 = -0.5$ and $\hat{\zeta}^5 = \hat{\beta}^1 = 0$ are obtained, which means that 50% loss in stabilizer has occurred.

6. CONCLUSIONS

In this paper, an effective approach to isolate the sensor and control surface/actuator failures affecting the innovation of Kalman filter was proposed and applied to an UAV dynamic model. To diagnose if the fault is a sensor fault or an actuator fault, linear adaptive TSKF insensitive to actuator faults is developed. In the proposed method, sensor faults are isolated by the normalized innovation of Kalman filter. Assuming that the effect of the faulty sensor on its own channel is more significant than on the other channels, a sensor isolation method is presented by transforming an *s*-dimensional innovation process to s one-dimensional processes. This paper also reported some results on the simultaneous estimation of the states and parameterized faults injected into the actuators of a linear model of an UAV using a linear adaptive TSKF An adaptive TSKF was modified for use to estimate the reduction of control effectiveness and the magnitude of stuck faults for a linear UAV model. The actuator faults are isolated and identified through the TSKF. Some simulation results on fault parameter estimation performed on a linear model of the longitudinal and lateral motion of the UAV were presented. The linear adaptive TSKF is successful in identifying the magnitude of the stuck fault and the percentage of the partial loss in the stabilizer. Control inputs have been excited by a pseudo random noise such that successful estimation of stuck magnitudes and loss of effectiveness can be achieved.

REFERENCES

Amoozgar M.H, A. Chamseddine and Y. Zhang (2013). Experimental Test of a Two-Stage Kalman Filter for Actuator Fault Detection and Diagnosis of an Unmanned Quadrotor Helicopter. *J. Intelligent Robot Systems*, **70**, 107–117.

Boskovic, J.D. and R.K.Mehra (2001). A robust adaptive reconfigurable flight control scheme for accommodation of control effector failures. *Proceedings of the American Control Conference,* Arlington, VA, 1127-1132.

Caliskan F., Y. Zhang, N.E. Wu and J. Y. Shin (2009). Estimation of actuator fault parameters in a nonlinear Boeing 747 model using a linear Two-Stage Kalman Filter. Preprints of the 7th IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes, Barcelona, Spain, 1408-1413.

Hajiyev Ch. and F. Caliskan (2003). Fault Diagnosis and Reconfiguration in Flight Control Systems. Boston Hardbound: Kluwer Academic Publishers.

Hajiyev Ch. and F. Caliskan (2005). Sensor and control surface/actuator failure detection and isolation applied to F-16 flight dynamic. Aircraft Engineering and Aerospace Technology, 77(2), 152-160.

Hajiyev Ch. and H.E. Soken (2012). Robust Estimation of UAV Dynamics in the Presence of Measurement Faults. *Journal of Aerospace Engıneerıng*, Vol. 25, No. 1, January, 80-89.

Keller J.K and M. Darouach, (1997). Optimal Two-Stage Kalman Filter in the Presence of Random Bias*, Automatica*, **33**(9):1745-1748.

Larson E.C., Jr. Parker, B. Eugene, B.R. Clark (2002). Model-based sensor and actuator fault detection and isolation. In: *Proceedings of the American Control Conference*. v 5. p. 4215-4219.

Maybeck P.S. (1999). Multiple model adaptive algorithms for detecting and compensating sensor and actuator/surface failures in aircraft flight control systems*. International Journal of Robust and Nonlinear Control*; 9(14): 1051-1070.

Shin, J.Y, N. E. Wu, and C. Belcastro (2004). Adaptive linear parameter varying control synthesis for actuator. *Journal of Guidance, Control, and Dynamics,* **27**(4):787-794.

Wu, N.E., S. Thavamani, Y. Zhang and M. Blanke, (2006). Sensor fault masking of a ship propulsion system, *Control Engineering Practice*, **14** (11), 1337–1345.

Wu N.E, Y. Zhang and K. Zhou (2000). Detection, estimation, and accommodation of loss of control effectiveness. *Int. J. Adapt. Control Signal Process*. **14**:775-795.

Yang, X, M. Michael, B. Arain, B. Upcroft, T. Gonzalez, F. Luis, and L. Mejias (2013). A UKF-based estimation strategy for actuator fault detection of UASs. *In Proceedings of the 2013 International Conference on Unmanned Aircraft Systems, ICUAS,* IEEE Control Society, Atlanta, Georgia, pp. 516-525.

Yechout, T. R., S.L. Morris, D.E. Bossert, and W.F. Hallgren (2003). Introduction to Aircraft Flight Mechanics: Performance, Static Stability, Dynamic Stability, and Classical Feedback Control, AIAA Education Series, Virginia, USA.

Zhang Y. and J. Jiang (2002). Active fault tolerant control system against partial actuator failures. *IEE Proceedings-Control Theory Applications*, **149**(1), 95-104.