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An Innovation Approach Based Sensor Fault Detection and Isolation

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Abstract: In this study, an innovation approach based new sensor Fault Detection and Isolation (FDI) method, which is sensitive to the changes in the innovation mean and covariance of the Kalman filter is proposed. The multiple measurement noise scale factors (MMNSFs) are used in this method as the monitoring statistics. Multiple measurement noise scale factors are determined in order to make it possible to perform the sensor fault detection and isolation operations simultaneously. Proposed innovation approach based sensor FDI algorithm with MMNSF is applied to the dynamic model of an Unmanned Aerial Vehicle (UAV) platform. The single sensor faults are considered. The proposed FDI algorithms are tested for the two different measurement malfunction scenarios; continuous bias at measurements, measurement noise increment.

Keywords: Fault detection; Fault isolation; Innovation sequence; Kalman filters; Scale factor; Estimation; Aerospace.

1. INTRODUCTION

Faults in dynamical systems can be detected with the aid of the innovation of Kalman filter. This approach proposed by Mehra, and Peschon (1971) can be pointed as the forerunning study in this area. The innovation sequence has the property that if the system operates normally the normalized innovation sequence of Kalman filter is a Gaussian white noise with a zero mean and 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 a decrease of instrument accuracy, an increase of background noise, etc., affect the characteristics of the normalized innovation sequence by changing its white noise nature, displacing its zero mean, and varying unit covariance matrix. Therefore, in this case, the fault detection problem is reduced to the problem of the fastest detection of the deviation of these characteristics from nominal. In literature an innovation approach for fault detection is discussed by many researchers (Gadzhiyev, 1992, 1994; Hajiyev and Caliskan, 2005; Caliskan and Hacizade, 2014). The advantages of these methods are as follow: they provide the monitoring of the correctness of the result obtained by the current working input actions; they do not require a priori information about the values of the changes in the statistical characteristics of the innovation sequence in case of fault; they allow one to solve the fault detection problem in real time; they require small computational expenditures for realization since they do not increase the dimension of the initial problem, in contrast to the most algorithmic methods.

In (Hajiyev and Caliskan, 2005) the sensor and control surface/actuator failures that affect the mean of the innovation have been studied. The Extended Kalman Filter (EKF) is developed for nonlinear flight dynamic estimation of an F-16 fighter and the effects of the sensor and control surface/actuator failures in the innovation sequence of the designed EKF are investigated. When the EKF is used, the decision statistics changes regardless the fault is in the sensors or in the control surfaces/actuators. However a Robust Kalman Filter (RKF) is used, it is possible to discriminate the sensor and control surface/actuator faults.

Testing, in real time, the innovation covariance matrix of the Kalman filter turns out to be a very complicated, since there are difficulties in the determination of the confidence domain for a random matrix. In (Gadzhiyev, 1992) a method is described for checking the sum of all elements of the inverted covariance matrix of the innovation sequence. In this work an approach based on the ratio of two quadratic forms of which matrices are theoretic and sample covariance matrices of Kalman filter innovation sequence is presented too. The optimal arguments of the quadratic forms are found to quickly detect the faults in the Kalman filter.

In (Gadzhiyev, 1994) for multidimensional dynamic systems a fault detection algorithm based on the confidence interval of the generalized variance of the Kalman filter innovation, is presented.

Most of the fault detection tests are based on the statistical properties of the eigenvalues of the sample covariance matrix (Malik, 2003; Zanella *et al.,* 2008). There exist some interesting results on the distribution and characteristic function of eigenvalues. But the application of the mentioned works to fault detection problem of multidimensional dynamic systems turns out to be very complicated since there are difficulties about determining the confidence domain (or intervals) for the eigenvalues of the random matrix.

In (Hajiyev, 2012) an operative method of testing the innovation covariance of the Kalman filter based on the Tracy–Widom distribution is proposed. The maximal eigenvalue of the random Wishart matrix is used as the monitoring statistic, and the testing problem is reduced to

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determine the asymptotics for the largest eigenvalue of the Wishart matrix. An algorithm for testing the largest eigenvalue based on the Tracy–Widom distribution is proposed and applied to the F-16 aircraft flight control system for detection of sensor and control surface faults.

In (Hajiyev, 2014) a new approach based on the generalized Rayleigh quotient for testing the innovation covariance of the Kalman filter is proposed. The generalized Rayleigh quotient of the vector under the sample and theoretical innovation covariance matrices are used in this study for the monitoring statistics. The proposed approach to the innovation covariance testing is used for the sensor/actuator fault detection problem in the AFTI/F-16 aircraft flight control system.

In this paper, an innovation approach based new sensor FDI method, which is sensitive to the changes in the innovation mean and covariance of the Kalman filter is proposed. As the difference from the existing innovation based FDI methods this approach allows to detect and isolate sensor faults simultaneously. The multiple measurement noise scale factors (MMNSF) are used in this method for the monitoring statistics. The proposed innovation approach based sensor FDI algorithm with MMNSF is applied for the model of dynamics of an unmanned aerial vehicle (UAV) platform. The proposed FDI algorithms are tested for two different measurement malfunction scenarios; continuous bias at measurements and measurement noise increment.

2. PRELIMINARIES

Let us consider the linear dynamic system described by the state equation

$$x(k+1) = Ax(k) + Bu(k) + Gw(k) \tag{1}$$

and measurement equation

$$z(k) = Hx(k) + V(k)\,, \tag{2}$$

where *x(k)* is an *N*-dimensional vector of system state; *A* is the $N\times N$ transition matrix of the system; B is the $N\times p$ control distribution matrix; u(k) is the p dimensional control input vector; *w(k)* is a random *r*-dimensional vector of disturbances (system noise); *G* is the $N\times r$ transition matrix of system noise; *z(k)* is the *n*-dimensional vector of measurements; *H* is the $n\times N$ matrix of measurements of the system; and *V(k)* is a random *n*-dimensional vector of measurement noise. Assume that random vectors *w(k)* and *V(*k*)* are Gaussian white noise. Their mean values and covariances are determined by the expressions

$$\begin{aligned} &E\left[w(k)\right]=0; E\left[V(k)\right]=0; E\left[w(k)w^T(j)\right]=Q(k)\delta(kj);\\ &E\left[V(k)V^T(j)\right]=R(k)\delta(kj). \end{aligned} \tag{3}$$

Here *E* is the operator of statistical expectation; *T* is the sign of transposition; and *δ(kj) is* the Kronecker delta symbol. Note that $\{w(k)\}$ and $\{V(k)\}$ are assumed mutually uncorrelated.

Apparently (Kalman, 1960), the optimum linear Kalman filter (LKF) that estimates the state vector of the system (1) is expressed with the following recursive equations system:

Equation of the estimation value,

$$\hat{x}(k/k) = \hat{x}(k/k-1) + K(k)\Delta(k) \tag{4}$$

where $\hat{x}(k/k-1) = A\hat{x}(k-1/k-1) + Bu(k-1)$ is the extrapolation value, $K(k)$ is the gain matrix of the LKF

$$K(k) = P(k/k-1)H^T(k)P_\Delta(k)^{-1} \tag{5}$$

$\Delta(k)$ is the innovation sequence

$$\Delta(k) = z(k) - H(k)\hat{x}(k/k-1) \tag{6}$$

$P_\Delta(k)$ is the innovation covariance

$$P_\Delta(k) = H(k)P(k/k-1)H(k) + R(k) \tag{7}$$

The covariance matrix of the estimation error is,

$$P(k/k) = \left[I - K(k)H(k)\right]P(k/k-1) \tag{8}$$

where I is the identity matrix.

The covariance matrix of the extrapolation error is,

$$P(k/k-1) = AP(k-1/k-1)A^T + GQ(k-1)G^T \tag{9}$$

3. INFLUENCE OF SENSOR FAULTS TO THE INNOVATION OF KALMAN FILTER

3.1. Influence of Sensor Biases to the Innovation

The following theorems are proved in this study.

Theorem 1. If the measurements are processed by the LKF (4)-(9) and a bias in measurement occurs at iteration step $k=\tau$, then at step $k=\tau$ the innovation bias is equal to the measurement bias.

Theorem 2. If the measurements are processed by the LKF (4)-(9) and a bias in measurement occurs at the iteration step $k=\tau$, then at the all $k>\tau$ steps the innovation bias is equal to the difference between the measurement bias and predicted observation bias.

To determine the unknown measurement bias from the innovation bias is not possible, because the predicted observation bias is also unknown.

3.2. Influence of Sensor Noise Increment to the Innovation

Let the measurements are processed by the LKF (4)-(9) and a noise increment in measurement occurs at the iteration step $k\geq\tau$. Noise increment can be simulated by multiplying the measurement noise with the constant $\gamma(k-\tau)$ $(\gamma(k-\tau)>1$ for $\forall\ k\geq\tau$). The measurement equation in this case can be written in the form:

$$z(k) = Hx(k) + \gamma(k-\tau)V(k) \tag{10}$$

where