Fault Detection and Isolation based on Robust Kalman Filter for Discrete-Time Systems with Stochastic and Norm-bounded Uncertainties

Amirhossein Barati[1], Mehdi Rahmani[1*]

[1] Department of Electrical Engineering, Imam Khomeini International University, Qazvin, Iran
[*]Corresponding author: mrahmani@eng.ikiu.ac.ir

ABSTRACT

This paper deals with the problem of fault detection and isolation for discrete time-varying systems with stochastic and bounded uncertainties, and in presence of noises in the plant and sensors. Faults can occur simultaneously or sequentially, so the designed filter has the ability to detect and isolate these faults, and handle the challenges posed by uncertainty and the effects of noises. In solving the problem of fault diagnosis, fault detection and isolation filter based on the robust Kalman filter is presented. For this purpose, a time-varying threshold is defined based on the upper bound of covariance of the residuals. This threshold helps in better performance and prevents misdiagnosis. In design of the fault detector, due to the number of outputs, fault detectors are designed. Moreover, by examining the residuals of the system, some conditions are obtained, which, by applying these conditions, a robust fault isolator is achieved. Finally, using three examples, the efficiency and performance of the proposed method are shown. In the first example, the performance of the proposed method is studied in the presence of uncertainty and noise, and in the second and third examples, the performance of the method is compared with other methods and the superiority of the proposed approach in the presence of uncertainties is shown.

KEYWORDS

Fault Detection, Fault Isolation, Robust Kalman Filter, Discrete-time system, uncertainty.

1. Introduction

A fault or defect in one part can destroy the performance of the whole system. Therefore, today, with the increasing complexity and size of systems, establishing security and increasing the reliability of advanced systems such as spacecraft, aircraft and chemical and nuclear processes is of great importance. Immediate fault detection in these systems is crucial to ensure security and increase reliability. Process and sensor noises as well as uncertainty in system parameters, challenge the problem of fault detection and isolation. Therefore, many attempts have been made to detect and isolate faults and different methods have been proposed in the literature. These methods can be divided into two categories: analytical and model-based methods. Many studies have been done using analytical and knowledge-based methods to diagnose defects, for instance, the presented method in [1] can detect faults based on the model and dynamic behavior of the car suspension system. In addition, model-based methods are divided into several categories [2]. In this regard, observer-based methods have attracted much attention [3].

In this paper, we intend to deal with the problem of fault detection and isolation in time-varying discrete systems, in the presence of two types of stochastic and norm-bounded uncertainties with sensor and process noises using a robust Kalman filter. In the presented fault detection and isolation method, we first introduce the robust least squares method. Then, we examine the fault detection conditions according to the created residues and provide a way to construct the threshold so that we do not have a false warning. Therefore, we examine the fault isolation conditions and consider some limitations in the design of a robust filter for fault detection and isolation. By considering these constraints, the system residues are obtained in such a way that they are only a function of the fault and noise, and these constraints reduce the effect of noise on the system residues.

2. Methodology

Considering the fault in the components and operators and the uncertainty in the parameters, the system is defined as follows:

$$x_{k+1} = (A_k + \delta A_k) x_k + B_k^u u_k + (B_k^n + \delta B_k^u) w_k + F f_k$$
$$y_{k+1} = (C_k + \delta C_k) x_k + (D_k + \delta D_k) v_k \quad (1)$$

According to the system introduced in (1) and the robust Kalman filter presented by Abolhassani and Rahmani in [4], the fault detection filter is defined as follows:

$$\hat{x}_{k+1|k} = (\hat{A}_k - L_k C_k)\hat{x}_{k|k-1} + L_k y_k$$
$$L_k = A_k F_k (C_k^T - S_k D_k^T) T_k \quad (2)$$

Now, the estimation error is defined as follows:

$$e_k = x_k - \hat{x}_{k|k-1} \quad (3)$$

To obtain F_k in (2), the following augmented system is introduced:

$$\tilde{x}_{k+1} = (\tilde{A}_k + \tilde{M}_k \Delta_k \tilde{E}_{a,k} + \tilde{N}_k \Delta_{a,k} \tilde{J}_{a,k})\tilde{x}_k + (\tilde{B}_k + \tilde{M}_k \Delta_k \tilde{E}_{b,k} + \tilde{N}_k \Delta_{b,k} \tilde{J}_{b,k})\theta_k \quad (4)$$

The parameter is achieved by solving the following optimization problem that minimizes the covariance of the above augmented system. More details are provided in [32].

$$\min_{F_k} trace\{\tilde{P}_{k+1}\}$$
$$s.t.$$
$$\begin{bmatrix} \tilde{P}_{k+1} - (\alpha_k + \beta_k)\tilde{M}_k \tilde{M}_k^T - (\xi_k + \zeta_k)\tilde{N}_k \tilde{N}_k^T & * & * \\ \hat{\tilde{P}}_k \tilde{A}_k^T & \hat{\tilde{P}}_k & * \\ \hat{\Theta}_k \tilde{B}_k^T & 0 & \hat{\Theta}_k \end{bmatrix}$$
$$F_k > 0 \quad (5)$$

By introducing the difference between the measured values and the estimated output values, the residual sequence is defined as follows:

$$z_k = y_k - \hat{y}_{k|k-1} \quad (6)$$

The upper bound of covariance is obtained as follows:

$$\tilde{P}_{\tilde{z}_k} \le \tilde{C}_k \hat{\tilde{P}}_{\tilde{z}_k} \tilde{C}_k^T + \tilde{D}_k \tilde{V}_k \tilde{D}_k^T + (\alpha_{2,k} + \beta_{2,k})\tilde{M}_{2,k}\tilde{M}_{2,k}^T - (\xi_{2,k} + \zeta_{2,k})\tilde{N}_{2,k}\tilde{N}_{2,k}^T \quad (7)$$

Values on the $\tilde{P}_{\tilde{z}_k}$ original diameter are associated with system residuals. Each of these values can be introduced to detect a fault in the system, so that the covariance values of the error associated with each case should not exceed its upper limit.

To isolate the fault at k + n, it is necessary to remove the fault effect in e_{k+n-1}. Now, if the following conditions are applied in solving the problem of convex optimization (5), the operation fault that occurred in the system can be isolated from the residual vectors.

$$(\hat{A}_{k+n-1} - L_{k+n-1} C_{k+n-1}) B_{k+n-2}^n = 0$$
$$(\hat{A}_{k+n-1} - L_{k+n-1} C_{k+n-1}) F = 0 \quad (8)$$

Then,

$$Z_{k+n} = C_{k+n}\varphi_k + n_k + (D_{k+n} + \delta D_{k+n}) v_k + C_{k+n} F f_{k+n-1} \quad (9)$$

Isolation and fault detection can be performed by

$$r_k = (C_{k+n} F)^{-1} z_{k+n}$$
$$r_k = f_{k+n-1} + \tilde{n}_k \quad (10)$$

3. Results and Discussion

In this section, two examples are given, in these examples, the performance of the presented method is compared with the methods in [5] and [6] respectively. In the first example, according to the matrix F, we apply two faults in presence of uncertainty in the form of $\sin(0.1k)$ with amplitude of 10 and a step with amplitude of 5 at K equal to 50 and 120, respectively, and consider the covariance of process noise and sensor as 0.2 and 0.1, respectively. As shown in Figure 1 and Figure 2, the proposed method outperforms the method presented in [5] in the presence of uncertainty.

In the second example, we compare the efficiency and performance of the proposed method with the method introduced in [6] in the presence of uncertainty in system parameters. The covariance of process and sensor noise is considered to be 0.1 and 0.01, respectively. As Figure 3 shows, the method presented in this paper more accurately identifies and isolates the fault that has occurred in the system.

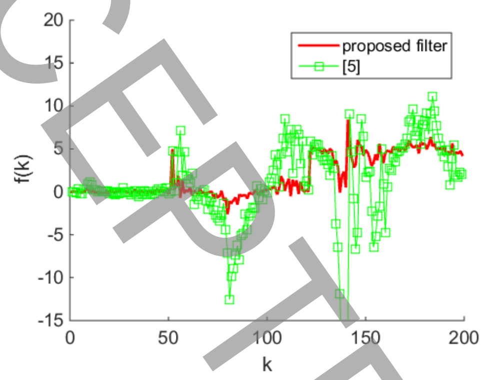

Figure 1. Performance of the proposed filter and filter [5] in sinusoidal fault isolation

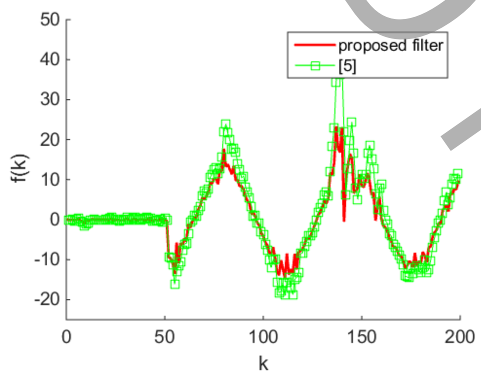

Figure 2. Performance of the proposed filter and filter [5] in step fault isolation

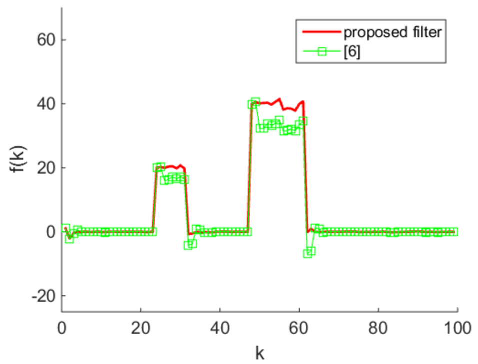

Figure 3. Performance of the proposed filter and filter [22] in step fault isolation

4. Conclusion

In this paper, by using the robust Kalman filter and examining the errors and residual of the system some conditions are achieved. By applying these conditions to solve the related convex optimization problem, a new robust method for fault detection and isolation in time-varying discrete systems with stochastic and norm bounded uncertainty is obtained. To detect the fault, the residual covariance was examined and by obtaining the upper bound of residual covariance, which is variable with time, and by comparing this time varying threshold with covariance of the residuals at any time, a new method for diagnosing the fault was introduced for these systems. Then, by applying the conditions obtained from the examination of residuals and some simplifications, a new robust method for fault isolation was proposed. Finally, the simulation results demonstrate the better performance and efficiency of the proposed approach in comparison with existing methods.

5. References

[1] m. shahab, M. Moavenian, Fault diagnosis based on model and dynamic behavior of vehicle suspension system, Amirkabir Journal of Mechanical Engineering, 52(1) (2020) 27-42.

[2] M. Kordestani, M. Saif, M.E. Orchard, R. Razavi-Far, K. Khorasani, Failure prognosis and applications—A survey of recent literature, IEEE transactions on reliability, (2019).

[3] H.H. Alhelou, Fault detection and isolation in power systems using unknown input observer, Advanced condition monitoring and fault diagnosis of electric machines, (2019) 38-58.

[4] M. Abolhasani, M. Rahmani, Robust Kalman filtering for discrete-time time-varying systems with stochastic and norm-bounded uncertainties, Journal of Dynamic Systems, Measurement, and Control, 140(3) (2018).

[5] J.-Y. Keller, Fault isolation filter design for linear stochastic systems, Automatica, 35(10) (1999) 1701-1706.

[6] A. Qiu, S. Shen, J. Zhang, Optimal intermittent fault diagnosis for discrete-time systems, in: 2016 35th Chinese Control Conference (CCC), IEEE, 2016, pp. 6814-6819.