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Fault Detection Based on Instantaneous Power Computation of Residue Application To Dynamical Systems

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Abstract

This article presents a robust strategy for sensor fault detection. This original approach is based on instantaneous power computation. An observer is used to estimate the output of the system and eliminate the unknown noise and external disturbance. The main contribution consists in developing an original strategy of fault detection based on instantaneous power calculation (FDIPC). The estimation procedure is proposed to detect potential sensor faults in linear hybrid systems. The effectiveness of the proposed approach is illustrated by numerical simulation examples. The simulation calculation was carried out using MATLAB®–SIMULINK® package and results have proven the excellent performance and have verified the validity and effectiveness of this approach in dynamic system

Keywords: Fault detection; reliability; FDI observer; instantaneous power; residue; control systems.

Introduction

Recently, fault detection (FD) techniques for discrete, hybrid and switching systems have gained increasing consideration world-wide. Fault detection is concerned with extraction of relevant features that indicate the existence of a fault, whereas, fault identification refers location and categorization of a fault or a set of faults. In recent years, fault detection has received more attention than ever before due to the increasing demand for more reliable dynamic systems because the failure of actuators, sensors and other components can result in performance degradation, severe damage of systems with the possibility of the loss of human lives. To avoid these consequences in the control systems, it is critical to detect and identify any possible faults at the earliest stage. Among all the methods for fault detection, one of the particular interesting techniques is the model-based fault detection observer approach [1] [2] [3] [4] [5] [6]. In general, when considering the problem of FD, two strategies can be found in the literature: hardware redundancy and software (or analytical) redundancy [7] [8]. However, the use of hardware redundancy is very expensive. FD techniques based on fault detection observer were proposed [9] [3] [6] as the fault detection observer design based on the H_∞/H index criterion [4] [10] [11]. Filters were also used in model-based fault detection [1][12] However, several deficiencies were detected in either the fault detection or isolation stages when the standard FDI theory was applied to solve this problem. This paper proposes a robust fault detection method based on instantaneous power calculation (FDIPC).

The structure of this paper is given as follows. The motivation and overview of the new fault detection approach are introduced in section II. Then, in section III, the observer design is given focus on the generation of estimated output. In section IV, FDIPC algorithm is exposed. Finally, the algorithm will be applied to a numerical example to assess the validity and the effectiveness of the proposed approach.

FDIPC Approach

Model-based FDI [13] [14] [15] is based on a certain set of numerical fault indicators, known as residuals $r(k)$, which are computed using the measured inputs $u(k)$ and outputs $y(k)$ of the monitored system.

$$r(k) = \Omega(y(k), u(k)) \tag{1}$$

Where Ω, is the residue generator function. This function allows computing the residual set at every time instant using the measurements of the system inputs and outputs. Ideally, residuals should be zero or less than a threshold that takes into account noise and model uncertainty when no fault is affecting the system.

The fault detection task consists of deciding if there is a fault affecting the monitored system by checking each residual $r_i(k)$ of the residual set against a threshold that takes into account model uncertainty, noise, and the unknown disturbances.

The result of this test applied to every residue $r_i(k)$ produces an observed fault signature,

$$\psi(k) = [\psi_1(k), \psi_2(k), \ldots, \psi_n(k)].$$

Basic way of obtaining these observed fault signals could be through a binary evaluation of every residual $r_i(k)$ against a threshold δ_i.

$$\psi i(k) = \begin{cases} 1 \ if \ |r_i| > \delta_i \\ 0 \ if \ |r_i| \leq \delta_i \end{cases} \tag{2}$$

The observed fault signature is then supplied to the fault isolation module that will try to isolate the fault so that a fault diagnosis can be given. This module is able to produce such a fault diagnosis since it has the knowledge about the binary relation between the considered fault hypothesis set $f(k) = f_1(k), f_2(k), \ldots, f_n(k)$ and the fault signal set $\psi(k)$. The presence of the noise produces chattering and restricting the relation between faults and fault signals to a binary one causes loss of useful information that can add fault distinguish ability and accurateness to the fault isolation algorithm, preventing possible wrong fault diagnosis results.

To avoid all these drawbacks, we add a module after the calculation of residue that contains the proposed algorithm. Figure.1 presents an overview of FDIPC design. The proposed scheme is composed by the plant (the controlled system), the observer which calculates the estimated state and outputs and the fault detection block which contains the proposed algorithm. The observer module estimates the state and the output of the system.

This is carried out using a filter. Consider the discrete time system described by the state space representation as follows :

$$\begin{cases} x[k + 1] = Ax[k] + Bu[k] + w[k] \\ y[k] = Cx[k] + v[k] \end{cases} \tag{3}$$

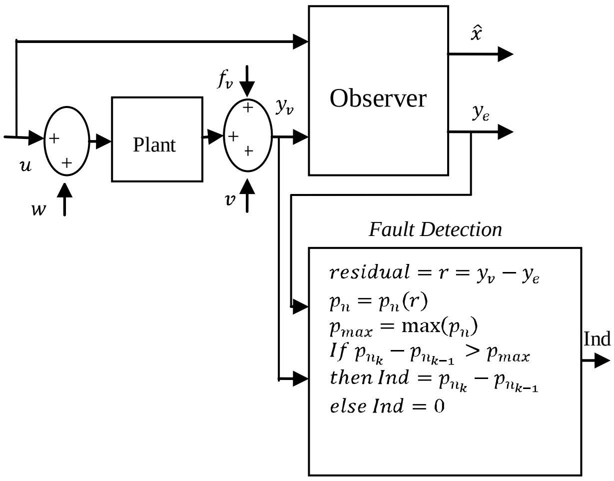

Figure 1: FDIPC Design

Where matrices *A*, *B* and *C* are the parameters of the system, $u\epsilon\mathbb{R}^{n_u}$ is the input variable, $x\epsilon\mathbb{R}^{n_x}$ and $y\epsilon\mathbb{R}^{n_y}$ represent the state and the output of the system respectively.

The process noise w and the measurement noise v are assumed to be white and uncorrelated with the input u. When sensor and actuator faults are considered, the state space representation (3) becomes :

$$\begin{cases} x[k + 1] = Ax[k] + Bu[k] + f_u(k) + w[k] \\ y_v[k] = Cx[k] + f_y(k) + v[k] \end{cases} \tag{4}$$

Where f_u and f_y are actuator and sensor faults and are assumed to be unknown constant additive numbers. The equations to estimate the state are given as follows :

$$\hat{x}[k] = \hat{x}[k-1] + M(y_v[k] - C\hat{x}[k-1]) \tag{5}$$

Where $\hat{x}[k]$is the estimate of $x[k]$ given past measurement up to $y_v[k-1]$ and $\hat{x}[k-1]$ is the updated estimate based on the last measurement $y_v[k]$. The measurement update then adjusts this prediction based on the new measurement $y_v[k + 1]$. Note that M is the innovation gain.

The correction term is the difference between the measurement and predicted values of $y_v[k + 1]$ is given by :

$$y_v[k + 1] - C\hat{x}[k + 1] \quad (6)$$

The innovation gain M is chosen to minimize the steady-state covariance of the estimation error given the noise covariances given as:

$E(w(k]w[k]^T) = Q$; $E(v[k]v[k]^T) = R$ and $E(w[k]v[k]^T) = O$. We combine the time and measurement update equations into one state space model as:

$$\hat{x}[k + 1] = A(I - MC)\hat{x}[k] + [B\ AM]\begin{bmatrix} u[k] \\ y_v[k] \end{bmatrix}$$
$$\hat{y}[k] = C(I - MC)\hat{x}[k] + CMy_v[k] \quad (7)$$

This observer generates an optimal estimate $\hat{y}[k]\ of\ y[k]$.

FDIPC fault detection is based on generating a residue comparing the measurements of physical variables $y_v(k)$of the process with their estimation $\hat{y}(k)$ provided by the associated system model (observer), i.e.

$$r(k) = |\hat{y}(k) - y_v(k)| \quad (8)$$

Where $y_v(k)$ is the true output and $\hat{y}(k)$ is the estimated output. $r\epsilon\mathbb{R}^{n_y}$ is the residue set then, in a non faulty scenario, $r(k)$ should be zero valued at every time instant k considering an ideal situation. Nevertheless, it will never be satisfied since the system can be affected by unknown inputs (i.e., noise, nuisance disturbances, etc.) and the model might be affected by some error assumptions (model errors) apart from its considered parameter uncertainty. Thus, the residue generated cannot be expected to be zero valued in a non faulty scenario. To perceive the variation of the residue in case of faulty scenario, we estimate first, the instantaneous power of the residue signal $r(k)$ in case of faultless system. The expression of instantaneous power p_n is given as follows.

$$p_n = \frac{1}{N}\sum_{n=k-N+1}^{k} r^2(k) \quad (9)$$

The instantaneous power of a physical system is defined monotone and bounded for each interval of the system $[a, b]$ i.e. [16].

The maximum power of the output instantaneous power of faultless operating system is noted p_{max} , it will represent the threshold in next step.

In a real operating system that will be affected by disturbances and faults, we estimate the output instantaneous power of $r(k)$ and instant verification of the difference $p_{n_k} - p_{n_{k-1}}$ of actual residue instantaneous power and past residue instantaneous power is calculated. Note Ind, the indicator of the presence of fault, so:

If $p_{n_k} - p_{n_{k-1}} > pmax$
then $Ind = p_{n_k} - p_{n_{k-1}}$ (10)
else $Ind = 0$

Simulation Results

The proposed FDIPC algorithm has been applied to the discrete time system with a state space model

$$\begin{cases} x[k+1] = Ax[k] + Bu[k] + fu(k) + w[k] \\ y_v[k] = Cx[k] + fy(k) + v[k] \end{cases}$$

Where $A = \begin{bmatrix} 0.156 & -0.310 & 0.216 \\ 1.000 & 0 & 0 \\ 0 & 1.000 & 0 \end{bmatrix}$,

$B = \begin{bmatrix} -0.725 \\ 0.140 \\ 0.681 \end{bmatrix}$ and $C = [1\ 0\ 1]$

$v[k]$ and $w[k]$ are Gaussian white noises

To obtain the estimated model of the system , the value of the innovation gain is given by:

The innovation gain $M = \begin{bmatrix} 0.367 \\ 0.068 \\ -0.395 \end{bmatrix}$

In the case study, first the output is estimated using real data from the sensors assuming no fault is affecting the system. Figure. 2 shows the true and estimated outputs and the noise v. We note that the residue is not null due to the presence of the process noise *w* and the measurement noise *v* which are assumed to be white and which are filtered by the observer. The maximum value of the instantaneous power of the residue in this case see Figure.3, is equal to.5.10^{-5} (threshold). In the case of occurrence of a fault (k =30), the true and estimated outputs are shown in Figure. 4 and the residue in Figure.5 We note the presence of a peak at the time of the occurrence of fault. The instantaneous power p_n represented in Figure. 6. shows clearly that regime changes at (k=30). The values of the instantaneous power p_n of the residue are so small because they independent of the values of the power of the system which can be very significant The FDIPC indicator *Ind* (Figure. 7) provides and proves this change in the status of the system. It's value is zero in absence of a fault. That is due to the choice of the threshold to calculate the indicator Ind. The threshold must be considered as the maximum of the instantaneous power of the residue in case of non faulty system.

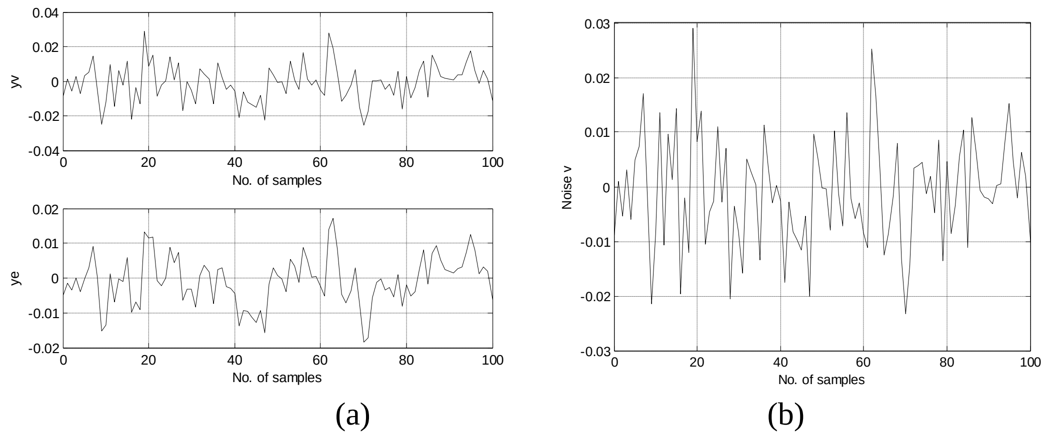

Figure 2: (a) The true and estimated output when no fault is affecting the system, (b) white noise added

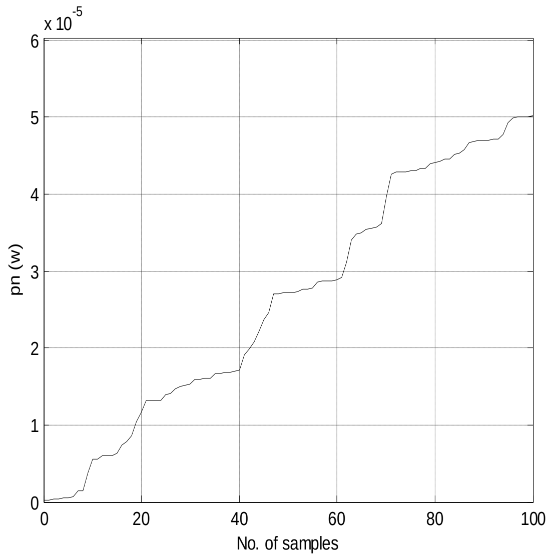

Figure 3: Instantaneous Power When No Fault Is Affecting The System

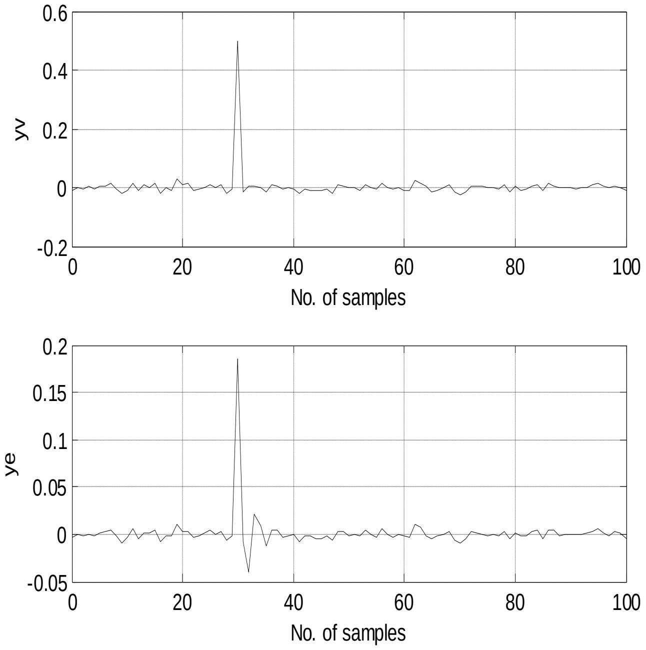

Figure 4: The True and Estimated Output When Fault Is Affecting The System

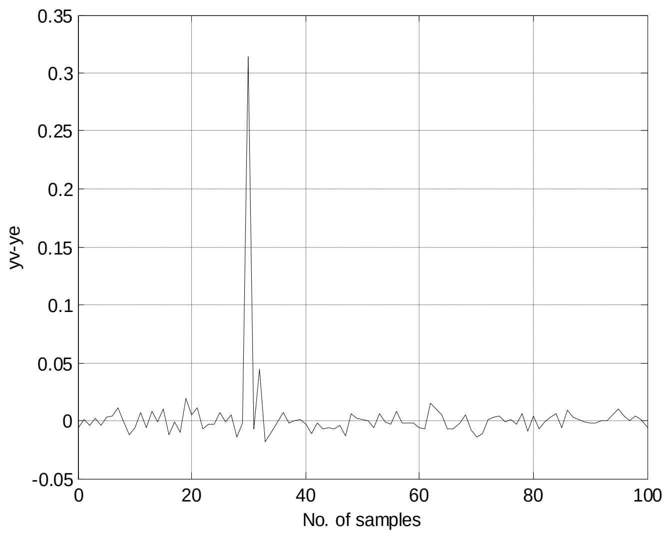

Figure 5: Residue When Fault Is Affecting The System

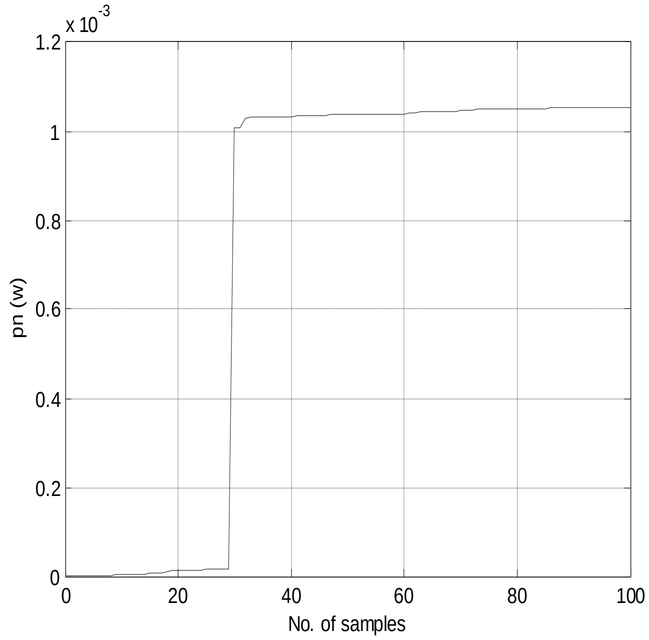

Figure 6: Instantaneous Power When Fault Is Affecting The System

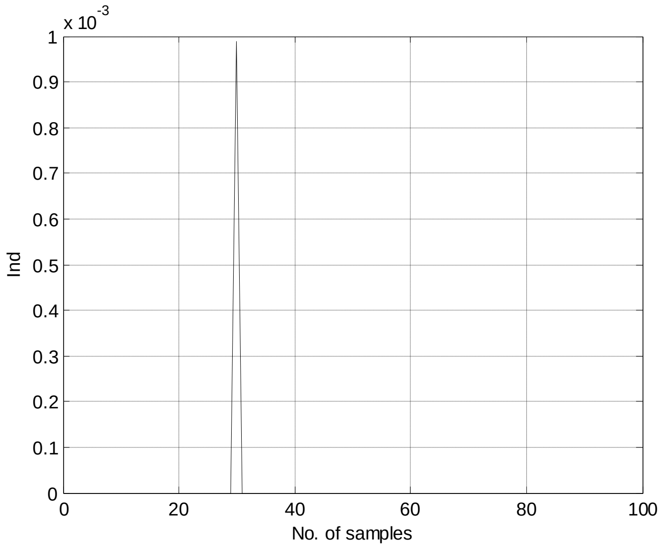

Figure 7: FDIPC Indicator When Fault Is Affecting The System

Conclusion

This paper considers the problem of fault detection. A FDIPC algorithm is presented based on instantaneous power computation of residue which is calculated upon the estimated model of the system. A scheme of this approach has been presented. The residue is computed by the comparison between the actual output of the system and its estimate. The detection block that contains the proposed algorithm permits to generate a signature on the state of the system. A numerical example shows that the proposed algorithm provides an effective solution for dynamic systems with uncertainties to detect occurring of fault.

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