

SUBSPACE METHOD FOR SENSOR FAULT DETECTION AND ISOLATION-APPLICATION TO GRINDING CIRCUIT MONITORING

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Abstract: Sensor fault detection and isolation method is proposed in this paper. The method is only based on the knowledge of the input and output data. Any parameter estimation nor system order determination are necessary. The proposed technique uses matrix projection in subspace framework. The sensitivity of the method to sensor faults is shown. The method is applied for sensor fault detection and isolation in a grinding circuit.

Keywords: sensor fault detection and isolation, subspace methods, linear discrete system, matrix projection, grinding circuit

1. INTRODUCTION

Fault detection and isolation methods have great interest in the last decade [1] and [4]. Parity space approach [5], [4] is a general tool for additive fault detection in linear systems. Parity space is based on algebraic projections and needs system model knowledge. It is well known that these methods are high sensitive to measurement, process noise and model uncertainties. Another method for fault detection and isolation is based on Kalman filtering or observer, but system model must be also available. If no model is available, Principal Components Analysis (PCA) can be used [5], [3]. In particular, by a SVD of input-output covariance matrix, data can be split into two parts indicating the underlying models and the residuals due to the noise and the errors. The statistical tests are made on the residuals to detect and isolate the faults. But PCA needs the determination of the system order, which estimation is not easy for stochastic systems.

Subspace techniques are known to be a straightforward method for system identification [8]. Recently subspace methods for fault detection and

isolation have been proposed. Subspace detection algorithm for vibration monitoring based on stochastic subspace identification method and the statistical local approach is proposed by Basseville *et al.* [2]. Their algorithms are established for linear stochastic systems without input. A recursive subspace method is proposed by Oku *et al.* for change detection in linear system dynamics [6] and [7]. In these recursive subspace methods, system parameters are estimated recursively and statistical tools are used to detect changes. A multiple sensor and actuator faults estimation by subspace identification method is proposed by Verdult *et al.* [9]. First, their method estimates fault free model and compares it to the current model also identified by subspace method.

To avoid system model estimation or system order determination, a new subspace method for sensor fault detection and isolation is proposed in this paper. This method is based only on the knowledge of the measured input-output. The proposed method uses matrix projection on a sliding window to generate residual vector which is zero mean in a fault free case and non zero mean in the presence of fault. This method is established for

linear discrete stable systems with input, output and system noise. The method is used to detect and isolate sensor fault on a simulated grinding circuit.

The paper is organized as follow: in section 2, fault detection and isolation problem is formulated. Fault detection technique is established in section 4. Sensor fault isolation technique is given in section 5. The application to monitoring a grinding circuit is made in section 6.

2. PROBLEM SETTING

The sensor fault detection and isolation problem is formulated in this part. Consider a linear discrete system described as:

$$\begin{aligned} x_{k+1} &= Ax_k + Bu_k^* + v_k \\ y_k &= Cx_k + Du_k^* + w_k \end{aligned} \quad (1)$$

where $u_k^* \in R^m$, $w_k, y_k \in R^\ell$ and $x_k, v_k \in R^n$. The output noise w_k and the state noise v_k are gaussian white noise and non correlated with the input u_k^* ; w_k is also not correlated with v_k . The input u_k^* is affected by a gaussian white noise \tilde{u}_k :

$$u_k^* = u_k + \tilde{u}_k \quad (2)$$

Note that u_k is the deterministic input given by the control computer and \tilde{u}_k is not correlated with u_k , v_k and w_k . Given q measurements of the input u_k and output y_k , the monitoring problem is to detect and isolate the sensor fault which affects the system. The faulty system can be written as:

$$\begin{aligned} x_{k+1} &= Ax_k + Bu_k^* + v_k \\ y_k &= Cx_k + Du_k^* + w_k + \varphi_k \\ \varphi_k &= (\varphi_k^1 \ \varphi_k^2 \ \dots \ \varphi_k^\ell)^T \in R^\ell \end{aligned} \quad (3)$$

where φ_k is a sensor fault.

The system matrices used to solve this identification problem are defined in the next section.

3. SYSTEM MATRIX DEFINITION

The sensor fault detection and isolation technique proposed in this paper uses some matrices defined below. We use two integers i and L which satisfy:

$$i < L \quad (4)$$

The deterministic and stochastic Markov parameter matrices are respectively defined as:

$$\begin{aligned} \bar{H}_i^d &= (CA^{i-1}B \ \dots \ CB \ D) \in R^{\ell \times m(i+1)} \\ \bar{H}_i^s &= (CA^{i-1} \ \dots \ C \ 0) \in R^{\ell \times m(i+1)} \end{aligned}$$

The input, output and output noise vectors are respectively defined as:

$$\begin{aligned} u_k^{*i} &= ((u_{k-i}^*)^T \ (u_{k-i+1}^*)^T \ \dots \ (u_k^*)^T)^T \in R^{m(i+1) \times 1} \\ y_{k,L} &= (y_k \ y_{k+1} \ \dots \ y_{k+L}) \in R^{\ell \times (L+1)} \\ w_{k,L} &= (w_k \ w_{k+1} \ \dots \ w_{k+L}) \in R^{\ell \times (L+1)} \end{aligned} \quad (5)$$

The system input block Hankel matrix is also defined as:

$$U_L^* = (u_k^{*i} \ u_{k+1}^{*i} \ \dots \ u_{k+L}^{*i}) \in R^{m(i+1) \times (L+1)}$$

The input block Hankel matrix depends on the system input given by the control computer $U_L \in R^{m(i+1) \times (L+1)}$, the input block noise matrix $\tilde{U}_L \in R^{m(i+1) \times (L+1)}$ and the system noise block Hankel matrix $V_L \in R^{n(i+1) \times (L+1)}$ are defined in the same manner.

As we mentioned earlier, we propose a new subspace method for sensor fault detection and isolation mainly based on matrix projection. This method is established in the next section.

4. FAULT DETECTION

The method is only based on the knowledge of system input and output data and any knowledge of system parameters is not necessary. It uses matrix projection in subspace framework. By matrix projection on sliding window, a gaussian zero mean residual vector is established, and an algorithm for change detection in signal mean is applied. The method is adapted to stable linear discrete systems.

4.1 Residuals generation

Using only the available input-output measurements, the residual vector is given by matrix projection. This residual vector is zero mean in fault free case and non zero mean if a fault occurs. To generate the residual vector, first we make approximation of the system output using Markov parameters. Next we project this output onto the orthogonal complement of the row space of the input and we obtain the residual matrix, which last column is selected as a residual vector. This projection removes the input influence and it remains only the noise effect. Let us establish first the expression of the output with the Markov parameters, for simplicity, this relation being given in noise free case.

For deterministic case ($\tilde{u}_k \equiv v_k \equiv w_k \equiv 0$) the output of the system (1) is expressed as follow:

$$y_k = CA^i x_{k-i} + CA^{i-1} Bu_{k-i}^* + \dots + CBu_{k-1}^* + Du_k^*$$

Due to the stability of the system, we can neglect the term $CA^i x_{k-i}$ if "i" is great enough. Thus:

$$y_k \simeq CA^{i-1} Bu_{k-i}^* + \dots + CBu_{k-1}^* + Du_k^* \quad (6)$$

By stacking the output, we obtain (with matrix definition in the previous section):

$$y_{k,L} \simeq \bar{H}_i^d U_L^* \quad (7)$$

where L is the size of the sliding window.

The previous relation can be extended to stochastic case as follow

$$y_{k,L} \simeq \bar{H}_i^d U_L + \bar{H}_i^d \tilde{U}_L + \bar{H}_i^s V_L + w_{k,L} \quad (8)$$

with

$$U_L^* = U_L + \tilde{U}_L \text{ (see (2))} \quad (9)$$

To remove the effect of the input, we project the row space of $y_{k,L}$ onto the orthogonal complement of the row space of U_L :

$$\begin{aligned} & y_{k,L} \Pi_{(U_L)^\perp} \simeq \\ & \bar{H}_i^d \tilde{U}_L \Pi_{(U_L)^\perp} + \bar{H}_i^s V_L \Pi_{(U_L)^\perp} + w_{k,L} \Pi_{(U_L)^\perp} \end{aligned} \quad (10)$$

where Π_{Q^\perp} is a geometric operator that projects the row space of a matrix onto the orthogonal complement of the row space of the matrix Q and is given by:

$$\Pi_{Q^\perp} = I - Q^T (QQ^T)^{(-)} Q \quad (11)$$

and $Q^{(-)}$ is the Moore-Penrose pseudo-inverse of the matrix Q .

Condition of existence

This projection can be made if the input is persistently excited and the integers i and L satisfy relation (4). If the integer i is near to L , the dimension of the complement of the row space of U_L is small, that can be made the fault detection problem more difficult. Then we choose

$$i \leq 1 + (L + 1 - \ell)/m \quad (12)$$

and the justification of this condition is given in the subsection "sensibility to sensor fault".

In equation (10) it remains only the influence of the noise. The matrix $y_{k,L} \Pi_{(U_L)^\perp}$ is a zero mean gaussian vector because it is a linear combination of a zero mean gaussian matrices \tilde{U}_L , V_L and $w_{k,L}$ and determinist matrices \bar{H}_i^d , \bar{H}_i^s and $\Pi_{(U_L)^\perp}$. If a fault occurs in the system, the last column of the matrix $y_{k,L} \Pi_{(U_L)^\perp}$ is not a zero mean processes (that is proven in the in subsection 4.3). Then, the fault can be detected by monitoring the mean of this column, thus we choose the last column as a residual vector. The selection of the last column of $y_{k,L} \Pi_{(U_L)^\perp}$ is achieve by the selection vector Z :

$$\begin{aligned} \varepsilon_k &= y_{k,L} \Pi_{(U_L)^\perp} Z, \quad Z = (0 \dots 0 1)^T \in R^{L \times 1} \\ \varepsilon_k &= \bar{H}_i^d \tilde{U}_L \Pi_{(U_L)^\perp} Z + \bar{H}_i^s V_L \Pi_{(U_L)^\perp} Z \\ &\quad + w_{k,L} \Pi_{(U_L)^\perp} Z \end{aligned}$$

ε_k is also a zero mean gaussian vector. If "L" is great, it can be proven that, the variance R_ε of the residual vector ε_k is obtained by the equation:

$$R_\varepsilon = \bar{H}_i^d R_{\tilde{u}} (\bar{H}_i^d)^T + \bar{H}_i^s R_v (\bar{H}_i^s)^T + R_w \quad (13)$$

with

$$\begin{aligned} R_v &= \mathbf{E} [V_L Z Z^T V_L^T], \quad R_{\tilde{u}} = \mathbf{E} [\tilde{U}_L Z Z^T \tilde{U}_L^T] \\ R_w &= \mathbf{E} [w_{k,L} Z Z^T w_{k,L}^T] \end{aligned} \quad (14)$$

Fault detection algorithm based on the zero mean hypothesis of the residual vector ε_k test is proposed in the following.

4.2 Fault detection method

It is established that, the residual vector ε_k is a zero mean process in fault free case ($\varepsilon_k \sim N(0, R_\varepsilon)$). In the next sub-section (sensitivity study cases), it is proven that the residual vector ε_k is a non zero mean process in the presence of a fault. Then testing the residual for the purpose of fault detection involves testing for the zero mean hypothesis. A χ^2 test is performed on the residual vector ε_k to detect change in the residual mean. Consider a vector ε_k , which elements are normally distributed with zero mean and R_ε covariance (see (13)). Let us set μ as the mean of the residual vector ε_k . The statistic $\varpi_k = \varepsilon_k^T R_\varepsilon^{-1} \varepsilon_k$ obeys a χ^2 distribution with ℓ degrees of freedom and can be tested as:

$$\text{if } \varpi_k \begin{cases} < \chi_{\ell,\alpha}^2 & \text{then no fault } (\mu = 0) \\ \geq \chi_{\ell,\alpha}^2 & \text{then fault } (\mu \neq 0) \end{cases} \quad (15)$$

The fault detection method is formulated below.

Algorithm 1

- ◀ Compute the projection $y_{k,L} \Pi_{(U_L)^\perp}$
- ◀ Select the last column $\varepsilon_k = y_{k,L} \Pi_{(U_L)^\perp} Z$
- ◀ Set $\varpi_k = \varepsilon_k^T R_\varepsilon^{-1} \varepsilon_k$
- ◀ If $\varpi_k \begin{cases} < \chi_{\ell,\alpha}^2 & \text{then no fault has occurred} \\ \geq \chi_{\ell,\alpha}^2 & \text{then a fault has occurred} \end{cases}$

A method applied to sensor fault detection is proposed in this section; in the following we show that the residual vector ε_k is affected by sensor fault.

4.3 Sensibility to sensor fault

The expression of the residual vector is given when a sensor fault occurs, and it is shown that this expression depends on the fault.

If the fault affects one sensor, the term φ_k differs from zero (3). We suppose the sensor fault appears at time instant $k+L$ on the h^{th} sensor. The system output (8) becomes:

$$y_{k,L} \simeq \bar{H}_i^d U_L + \bar{H}_i^d \tilde{U}_L + \bar{H}_i^s V_L + w_{k,L} + \Phi \quad (16)$$

where Φ is the fault bloc Hankel matrix defined as:

$$\Phi = \begin{pmatrix} 0 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & \dots & 0 & \varphi_{k+L}^h \\ \vdots & \vdots & \vdots & \vdots \\ 0 & \dots & 0 & 0 \end{pmatrix} \in R^{\ell \times L} \quad (17)$$

If we project the system output onto the orthogonal complement of the row space of U_L , we have:

$$\begin{aligned} y_{k,L} \Pi_{(U_L)^\perp} &\simeq \bar{H}_i^d \tilde{U}_L \Pi_{(U_L)^\perp} + \bar{H}_i^s V_L \Pi_{(U_L)^\perp} + \\ & w_{k,L} \Pi_{(U_L)^\perp} + \Phi \Pi_{(U_L)^\perp} \end{aligned}$$

and the mathematical expectation of this projection become :

$$\mathbf{E} \left[y_{k,L} \Pi_{(U_L)^\perp} \right] = \Phi \Pi_{(U_L)^\perp} \quad (18)$$

since w_k , v_k and \tilde{u}_k are zero mean process and independent from u_k .

Condition of sensibility to sensor fault

Let us analyze the additive term $\Phi \Pi_{(U_L)^\perp}$ (we set $P = U_L^T (U_L U_L^T)^{-1} U_L$):

$$\begin{aligned} \Phi \Pi_{(U_L)^\perp} &= \Phi - \Phi P \quad (19) \\ &= \begin{pmatrix} 0 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & \dots & 0 & \varphi_{k+L}^h - \varphi_{k+L}^h P(h, L) \\ \vdots & \vdots & \vdots & \vdots \\ 0 & \dots & 0 & 0 \end{pmatrix} \quad (20) \end{aligned}$$

where $P(i,j)$ denotes the element of the matrix P in line i and column j . The term $\varphi_{k+L}^h - \varphi_{k+L}^h P(h, L)$ takes the value :

- φ_{k+L}^h , if :

$$\text{span}(\Phi) \subset \text{span}(\Pi_{(U_L)^\perp}) \quad (21)$$

- 0, if :

$$\text{span}(\Phi) \subset \text{span}(\Pi_{U_L}) \quad (22)$$

- $\varphi_{k+L}^h - \varphi_{k+L}^h P(h, L)$, with :

$$0 < \|\varphi_{k+L}^h - \varphi_{k+L}^h P(h, L)\| \leq \|\varphi_{k+L}^h\| \quad (23)$$

if conditions (22) and (21) are not satisfied (since $P(h, L)$ is a projection matrix)

with $\text{span}(Q)$ denotes the row space of the matrix Q .

Then the residual ε_k is sensitive to the fault if $\text{span}(\Phi) \not\subset \text{span}(\Pi_{U_L})$, and the maximum sensitivity is obtain if condition ((21) holds. Equation (20) shows that, the fault matrix $\Phi \Pi_{(U_L)^\perp}$ affects only the last column of $y_{k,L} \Pi_{(U_L)^\perp}$, that justifies the selection of this column as residual vector.

Condition on row space dimension

The condition (21) implies that:

$$\dim(\text{span}(\Phi)) \leq \dim(\text{span}(\Pi_{(U_L)^\perp})) \quad (24)$$

where $\dim(Q)$ is the dimension of the subspace Q . The dimension of the subspaces used in (24) is determined below. It is obvious that

$$\dim(\text{span}(\Phi)) = \ell \quad (25)$$

We have also the equality: $\dim(\text{span}(U_L)) = m(i+1)$ dues to the persistently excitation of the input. Moreover, we have the property:

$$\dim(\text{span}(U_L)) + \dim(\text{span}(\Pi_{(U_L)^\perp})) = L + 1 \quad (26)$$

from which we deduce:

$$\dim(\text{span}(\Pi_{(U_L)^\perp})) = L + 1 - m(i+1) \quad (27)$$

Finally, from (24), (25) and (27), we obtain the relation (12).

5. SENSOR FAULT ISOLATION

If a fault is detected in a system, it is necessary to determine the cause of the failure. In the sensor fault case, that implies to find the faulty sensors. The sensor fault isolation technique proposed here is derived from the previous detection method. It uses the residuals given by the detection algorithm. When a fault occurs on a sensor, only the corresponding row in the additive fault matrix in relation (20) is not null, then only this line is corrupted in the residual vector. It is obvious that if we consider the rows of the residual vector ε_k one by one, we can determine the faulty sensor. Let us define the scalar residual of the h^{th} ($h = 1, \dots, \ell$) sensor by:

$$\varepsilon_k^h = S_h \varepsilon_k = S_h y_{k,L} \Pi_{(U_L)^\perp} Z \quad (28)$$

where S_h is the selector vector defined by:

$$S_h = (0 \dots 1 \dots 0) \in R^{1 \times \ell} \quad (29)$$

which contains one in column h and zero everywhere else. ε_k^h corresponds to the h^{th} element of the residual vector ε_k .

As in the residual vector case, it can be proven that ε_k^h is a gaussian zero mean distributed scalar with variance

$$R_\lambda = S_h \bar{H}_i^d R_u (S_h \bar{H}_i^d)^T + S_h \bar{H}_i^s R_v (S_h \bar{H}_i^d)^T + S_h R_w S_h^T \quad (30)$$

Any algorithm of change detection (see [1]) in the mean of a signal can be applied for sensor fault isolation. Here, finite moving average (FMA) algorithm is used for fault isolation. In the following, we relate briefly this algorithm.

Finite moving average algorithm

Consider the causal filtering for a zero mean white (see [1]):

$$g_k^h = \sum_{r=0}^{N-1} \gamma_r \varepsilon_k^h, \quad \gamma_r = \beta(1-\beta)^r, \quad 0 < \beta \leq 1 \quad (31)$$

Before the unknown change time t_a , the parameter μ^h (the mean μ^h of ε_k^h) is equal to μ_0^h , and after the change it is equal to $\mu_1^h \neq \mu_0^h$.

The alarm time is defined by the following stopping rule:

$$t_a = \min\{k : g_k^h \geq \eta^h\}$$

with η^h is a conveniently chosen threshold.

The sensor fault isolation method is summarized in algorithm 2 below.

Algorithm 2

- ◀ Compute the projection $y_{k,L} \Pi_{(U_L)^\perp}$
- ◀ Select a scalar residual $\varepsilon_k^h = S_h y_{k,L} \Pi_{(U_L)^\perp} Z$
- ◀ Implement the FMA algorithm
- ◀ If $g_k^h \begin{cases} < \eta^h \\ \geq \eta^h \end{cases}$ then no fault has occurred
then a fault has occurred

6. APPLICATION TO MONITORING AN ORE GRINDING CIRCUIT

The sensor fault detection and isolation technique proposed in this paper is used to monitor the grinding circuit described in figure 6. The target is to detect and isolate the sensor faults which affect the simulated grinding circuit. The grinding process is described in the following.

First the input flow $u(t)$ is sorted out in the first screen S_1 in two parts: $(1 - k_0)u(t)$ and $k_0u(t)$ corresponding to the fine and the coarse particles. The coarse particles $k_0u(t)$ are ground in the first crusher G_1 and the output $x_1(t)$ is also sorted by the second screen S_2 in two parts: the coarse $k_1x_1(t)$ and the fine $\{(1 - k_1)x_1(t) = y_1(t)\}$. The coarse particles obtained $k_1x_1(t)$ are mixed with the fine previously obtained $(1 - k_0)u(t)$ and ground in the second crusher G_2 . The result $x_2(t)$ is also sorted out in two parts: the fine $\{(1 - k_2)x_2(t) = y_2(t)\}$ and the coarse $k_2x_2(t)$. The coarse particles $k_2x_2(t)$ are ground, the output x_3 is sorted in two parts the coarse $k_3x_3(t)$ and the fine $\{(1 - k_3)x_3(t) = y_3(t)\}$. The coarse particles $k_3x_3(t)$ are returned and mixed with the first coarse selected $k_0u(t)$ and so on ...

The grinding circuit state equation is established first in continuous time "t" and discretized later. The crushers are first order linear systems and related by the frequency relation:

$$x_h(s) = \frac{1}{1 + sT_h} Q_e^h(s), h = 1, 2, 3 \quad (32)$$

where $Q_e^h(s)$ is the input of the h^{th} grinding unit and $x_h(s)$ is the output of the same grinding unit. We have for the three grinding units:

$$\begin{aligned} \begin{pmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \end{pmatrix} &= \begin{pmatrix} -\frac{1}{T_1} & 0 & \frac{k_3}{T_1} \\ \frac{k_1}{T_2} & -\frac{1}{T_2} & 0 \\ 0 & \frac{k_2}{T_3} & -\frac{1}{T_3} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} \\ &+ \begin{pmatrix} \frac{k_0}{T_1} \\ \frac{1-k_0}{T_2} \\ 0 \end{pmatrix} u \\ \begin{pmatrix} y_1 \\ y_2 \\ y_3 \end{pmatrix} &= \begin{pmatrix} 1 - k_1 & 0 & 0 \\ 0 & 1 - k_2 & 0 \\ 0 & 0 & 1 - k_3 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} \end{aligned}$$

with the following numerical values: $T_1=5$, $T_2=1$, $T_3=2$, $K_0=0.4$, $K_1=0.5$, $K_2=0.1$ and $K_3=0.3$.

The above system is discretized with sample time $T_e=0.97$ and becomes:

$$\begin{aligned} \begin{pmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \end{pmatrix} &= \begin{pmatrix} 0.82 & 0.00 & 0.04 \\ 0.28 & 0.38 & 0.01 \\ 0.01 & 0.02 & 0.62 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} + \begin{pmatrix} 0.07 \\ 0.39 \\ 0.01 \end{pmatrix} u_k^* \\ \begin{pmatrix} y_1 \\ y_2 \\ y_3 \end{pmatrix} &= \begin{pmatrix} 0.6 & 0 & 0 \\ 0 & 0.9 & 0 \\ 0 & 0 & 0.7 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} + w_k \quad (33) \end{aligned}$$

where u_k^* is given in Eq (2). The sensor faults affecting the simulated system:

- the first and third outputs are simultaneous affected on interval [2000, 2050] by a sensor fault $\varphi_k^1 = 0.25 y_{\max}^1$, $\varphi_k^3 = 0.25 y_{\max}^3$, where y_{\max}^h ($h = 1, \dots, \ell$) is the maximum value of the h^{th} output and φ_k^h is the fault on the h^{th} sensor (see (3)).
- on interval [3000, 3050] the second sensor is affected by a sensor fault $\varphi_k^2 = 0.25 y_{\max}^2$.
- the second and the third outputs are affected simultaneous on interval [4000, 4050] by a sensor fault $\varphi_k^2 = 0.25 y_{\max}^2$, $\varphi_k^3 = 0.25 y_{\max}^3$.
- the signal-to-noise ratios $RSB(y_k^h, w_k^h)$ with respect to the signal y_k^h (the h^{th} output) and the noise w_k^h (the h^{th} output noise) are: $RSB(y_k^1, w_k^1) = 21.0$, $RSB(y_k^2, w_k^2) = 21.3$, $RSB(y_k^3, w_k^3) = 21.2$.
- the input signal-to-noise ratio $RSB(u_k, \tilde{u}_k)$ with respect to the signal u_k and the noise \tilde{u}_k is: $RSB(u_k, \tilde{u}_k) = 21.2$. Since the system matrix C is diagonal, the system noise is equivalent to the output noise then we set $v_k=0$.

We set $i=13$, $L=43$ and $\alpha=0.9999$ in algorithm 1, $N = L$ in algorithm 2 and $\beta=0.05$ in FMA algorithm. The change detection technique is illustrated in figure 4. It shows that all simulated faults are detected. In figure 3, we observe that the residuals are sensible to the faults, and only those corresponding to the faulty sensors are corrupted. The sensor fault isolation method result is shown in figure 5. In this figure, the faulty sensors are identify in any case.

7. CONCLUSION

A sensor fault detection technique is proposed in the paper. The method is based on matrix projection on a sliding window and uses state space model in subspace framework. System parameter knowledge is not necessary to perform this technique. The sensibility of the fault detection method is shown. Sensor fault isolation method based on the proposed detection technique is also given. The method does not suffer for the model uncertainties because no model is used. It takes into account also the input, output and process noises. The sensor fault detection and isolation method proposed in the paper is used to validate the data of a grinding circuit.

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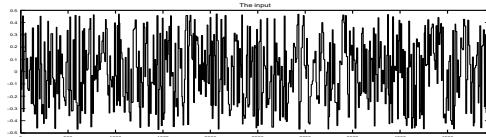


Fig. 1. the system input

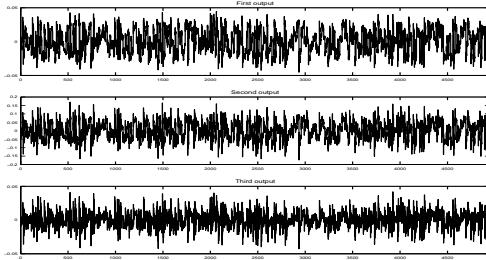


Fig. 2. the system output

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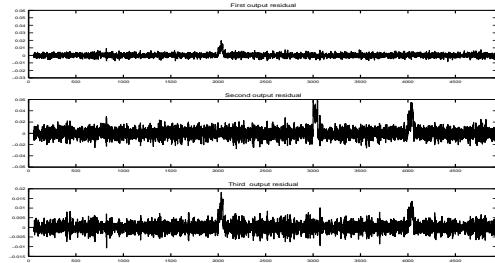


Fig. 3. residual vector used in algorithm 1

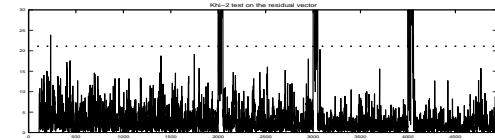


Fig. 4. fault detection by algorithm 1

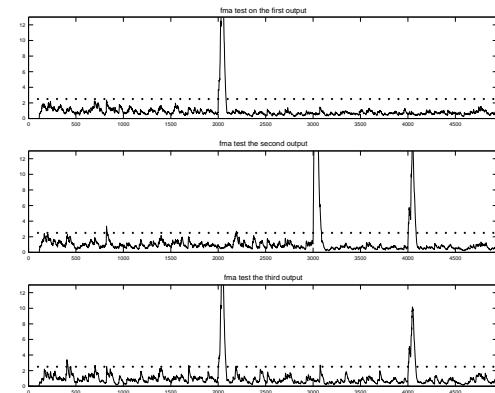


Fig. 5. sensor fault isolation by algorithm 2

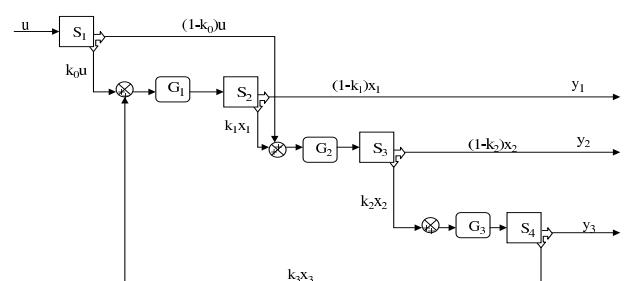


Fig. 6. the grinding circuit