

Research Article

Actuator Fault Diagnosis with Robustness to Sensor Distortion

Qinghua Zhang

INRIA-IRISA, Campus de Beaulieu, 35042 Rennes Cedex, France

Correspondence should be addressed to Qinghua Zhang, zhang@irisa.fr

Received 1 April 2007; Revised 15 August 2007; Accepted 11 November 2007

Recommended by Jakob Stoustrup

Actuator fault diagnosis is often studied under strong assumptions on available sensors. Typically, it is assumed that the sensors are either fault free or sufficiently redundant. The purpose of this paper is to present a new method for *actuator* fault diagnosis which is robust to *sensor* distortion. It does not require sensor redundancy to compensate sensor distortion. The essential assumption is that sensor distortions are strictly monotonous. Despite the nonlinear and unknown nature of distortions, such sensors still provide useful information for fault diagnosis. The robustness of the presented diagnosis method is analyzed, as well as its ability to detect actuator faults. A numerical example is provided to illustrate its efficiency.

Copyright © 2008 Qinghua Zhang. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

1. INTRODUCTION

In the design of modern control systems, fault diagnosis is often considered for component faults, sensor faults, and actuator faults. Various methods for fault diagnosis are generally based on the processing of sensor signals [1–3]. Many methods for *actuator* fault diagnosis assume reliable fault-free *sensors*, see, for instance, [4, 5]. For methods simultaneously dealing with actuator and sensor faults, it is typically assumed that there is sufficient redundancy among the sensors such that at any moment, the valid sensors can provide the information required for faults diagnosis. For mass production, it is important to use as less sensors as possible to reduce production cost. In such situations, fault diagnosis cannot uniquely rely on redundant sensors. Moreover, still for the purpose of cost reduction, sensors used in mass production may be highly nonlinear. If the sensor nonlinearity is well known, it can often be electronically compensated. Unfortunately, sometimes sensor nonlinearity varies within the production, and for each piece in use, the nonlinearity varies during its normal life duration. For example, most oxygen sensors used in cars equipped with catalytic converters are highly nonlinear. They roughly indicate if the oxygen concentration is over or below a reference value. Nevertheless, such sensors are sufficient for the purpose of engine control. It is then important to develop fault diagnosis methods relying on the same sensors. In this paper, unknown nonlinear behaviors of sensors are generally called *sensor distortion*.

The purpose of this paper is to present a method for actuator fault diagnosis which is robust to sensor distortion. It is assumed that each sensor can be affected by an *unknown* and *arbitrary*, but *strictly monotonous*, nonlinearity. The monotonousness is a weak assumption since any non monotonous distortion would make the sensor information useless. Remark that saturation is not a strictly monotonous nonlinearity, and thus is excluded in the proposed method. Nevertheless, a correctly working sensor should not be saturated when it is in its normal working range.

Robust methods for fault diagnosis has been studied in different contexts by many authors. In [6], a method based on adaptive wavelet analysis is proposed. The method studied in [7] uses generalized frequency response functions. Kullback discrimination information is used as a fault detection index in [8]. In [9], some faults of induction motors are detected by Fourier analysis of frequency signatures. (See the references cited in these publications for more information.) Compared to these existing results, the novelty of the method presented in this paper is its ability to deal with unknown nonlinear sensor distortions without requiring sensor redundancy.

The preliminary results presented in [10] are further developed in this paper, in particular, the analysis of the proposed robust detection method is completed with the characterization of the faults which can be detected.

The paper is organized as follows. The problem considered in this paper is formulated in Section 2. Fault detection

and isolation are, respectively, studied in Sections 3 and 4. A numerical example is presented in Section 5. Some concluding remarks are given in Section 6.

2. PROBLEM STATEMENT

The considered linear state-space system with sensor distortion is formulated as

$$\dot{x}(t) = Ax(t) + B \operatorname{diag}(u(t))\theta + w(t), \quad (1a)$$

$$z(t) = Cx(t) + v(t), \quad (1b)$$

$$y(t) = h(z(t)), \quad (1c)$$

where $x(t) \in \mathbb{R}^n$ is the state, $u(t) \in \mathbb{R}^l$ the input, $z(t) \in \mathbb{R}^m$ the output before sensor distortion, $y(t) \in \mathbb{R}^m$ the output after sensor distortion, and $w(t) \in \mathbb{R}^n$ and $v(t) \in \mathbb{R}^m$ represent bounded modeling uncertainties. The notation $\operatorname{diag}(u(t))$ denotes the diagonal matrix formed by the components of the input vector $u(t)$, and the vector $\theta \in \mathbb{R}^l$ is a coefficient vector introduced to describe the efficiency loss of actuators (multiplicative actuator faults). For fault-free actuators, θ takes the nominal value θ_0 .

For notation simplicity, the parenthesis (t) of the time-dependent variables will not be written unless necessary.

Sensor distortion is modeled by the component-wisely defined nonlinear function h : let z_i and y_i be, respectively, the i th component of z and y , $i = 1, \dots, m$, then

$$y_i = h_i(z_i). \quad (2)$$

Assumption 1. Each sensor distortion $h_i : \mathbb{R} \rightarrow \mathbb{R}$ is an unknown, but a strictly monotonously increasing, function. In other words, for any $\xi_1, \xi_2 \in \mathbb{R}$,

$$\xi_1 < \xi_2 \implies h_i(\xi_1) < h_i(\xi_2). \quad (3)$$

Assumption 2. The system dynamics matrix A is asymptotically stable, that is, the eigenvalues of A have negative real parts.

Remark 1. No additive uncertainty is assumed in the sensor distortion equation (1c) since the arbitrary unknown monotonous nonlinear function can take into account some sensor distortion uncertainty. On the other hand, if it is assumed that

$$y = h(z) + \varepsilon, \quad (4)$$

where ε is some additive uncertainty, define

$$\begin{aligned} \tilde{v} &= h^{-1}[h(Cx + v) + \varepsilon] - Cx, \\ \tilde{z} &= Cx + \tilde{v}, \end{aligned} \quad (5)$$

then (4) can be replaced by

$$y = h(\tilde{z}) \quad (6)$$

which is in the form of (1c). Of course, in order to limit \tilde{v} , some regularity of h should be assumed.

With the above formulation, the problem considered in this paper is the detection and isolation of multiplicative actuator faults, modeled as changes in the coefficient vector θ , despite the unknown sensor distortions.

3. FAULT DETECTION

The main difficulty of the problem formulated in the previous section is caused by the *unknown* sensor distortions. The key question is how to use the information provided by such sensors. Because of the unknown nature of h_i , for each measured value of $y_i = h_i(z_i)$, the corresponding value of z_i is completely unknown, and even the sign of z_i is unknown. The strict monotonousness of h_i assumed in Assumption 1 is not helpful in this aspect. However, it is important to make the following observation. For any two time instants t and τ , Assumption 1 implies that

$$\operatorname{sign}[z_i(t) - z_i(\tau)] = \operatorname{sign}[y_i(t) - y_i(\tau)]. \quad (7)$$

In other words, the relative sign of z_i at different time instants is known from the sensor output y_i measured at these time instants. Remark that t and τ are two arbitrary and independent time instants, and either one can be earlier than the other one. Since the absolute value $|z_i(t) - z_i(\tau)|$ is completely unknown, the relative sign is thus the only information about $z_i(t) - z_i(\tau)$ provided by the sensor output. This information will be the basis for the design of fault detection and isolation algorithms in this paper. Such information can also be used for the identification of Wiener systems [11].

Let $Z(s)$, $U(s)$, $W(s)$, and $V(s)$ be, respectively, the Laplace transforms of $z(t)$, $u(t)$, $w(t)$, and $v(t)$. It is then derived from (1a), (1b), and (1c) (by assuming zero initial state) that

$$Z(s) = C(sI - A)^{-1}B \operatorname{diag}(U(s))\theta + C(sI - A)^{-1}W(s) + V(s). \quad (8)$$

Define

$$\Phi(t) = \mathcal{L}^{-1}\left[C(sI - A)^{-1}B \operatorname{diag}(U(s))\right], \quad (9)$$

$$\zeta(t) = \mathcal{L}^{-1}\left[C(sI - A)^{-1}W(s) + V(s)\right], \quad (10)$$

where \mathcal{L}^{-1} is the inverse Laplace transform operator. Then

$$z(t) = \Phi(t)\theta + \zeta(t), \quad (11a)$$

$$y(t) = h(z(t)). \quad (11b)$$

Notice that $\Phi(t) \in \mathbb{R}^{m \times l}$ depends on $u(t)$ and can be computed through (9), whereas $\zeta(t) \in \mathbb{R}^m$ depends on modeling uncertainties $w(t)$, $v(t)$ and is unknown.

Remark 2. Zero initial condition of the state x has been assumed when (8) was derived. The asymptotic stability condition (Assumption 2) is not explicitly used in the above reasoning, but it ensures well-behaved computation of Φ through (9). To some extent, this stability condition allows also to tolerate nonzero initial states which are asymptotically forgotten. If the system was not asymptotically stable, then, in principle, an observer should be used in the computation of Φ . However, it is difficult to design observers with sensors distorted by unknown nonlinear functions.

Let ϕ_i be the i th row of Φ and ζ_i be the i th component of ζ , then the i th row of (11a) writes

$$z_i(t) = \phi_i(t)\theta + \zeta_i(t). \quad (12)$$

For any two time instants t and τ , it is obvious that

$$\text{sign}[z_i(t) - z_i(\tau)][z_i(t) - z_i(\tau)] \geq 0. \quad (13)$$

Substitute $z_i(t)$ and $z_i(\tau)$ with the last equality, then, for constant θ ,

$$\text{sign}[z_i(t) - z_i(\tau)][(\phi_i(t) - \phi_i(\tau))\theta + \zeta_i(t) - \zeta_i(\tau)] \geq 0. \quad (14)$$

Remind the relative sign equality (7), then

$$\text{sign}[y_i(t) - y_i(\tau)][(\phi_i(t) - \phi_i(\tau))\theta + \zeta_i(t) - \zeta_i(\tau)] \geq 0, \quad (15)$$

or equivalently

$$\begin{aligned} & -\text{sign}[y_i(t) - y_i(\tau)][\phi_i(t) - \phi_i(\tau)]\theta \\ & \leq \text{sign}[y_i(t) - y_i(\tau)][\zeta_i(t) - \zeta_i(\tau)]. \end{aligned} \quad (16)$$

Let θ_0 be the nominal value of θ (corresponding to fault-free actuators), a residual $r_i(t, \tau)$ for actuator fault detection can be generated as

$$r_i(t, \tau) = -\text{sign}[y_i(t) - y_i(\tau)][\phi_i(t) - \phi_i(\tau)]\theta_0. \quad (17)$$

It then follows from (16) that, in the fault-free case,

$$r_i(t, \tau) \leq \text{sign}[y_i(t) - y_i(\tau)][\zeta_i(t) - \zeta_i(\tau)]. \quad (18)$$

This result leads to the following proposition.

Proposition 1. *If $|\zeta_i(t)| \leq \lambda$ for some constant λ and any t , then the residual $r_i(t, \tau)$ defined in (17) satisfies, in the fault-free case, that is, $\theta = \theta_0$, the inequality*

$$r_i(t, \tau) \leq 2\lambda. \quad (19)$$

Proof. Let us first consider the case $y_i(t) \neq y_i(\tau)$, then it follows from the inequality (18) that

$$\begin{aligned} r_i(t, \tau) & \leq |r_i(t, \tau)| \\ & \leq |\zeta_i(t) - \zeta_i(\tau)| \\ & \leq |\zeta_i(t)| + |\zeta_i(\tau)| \leq 2\lambda. \end{aligned} \quad (20)$$

Now for the case $y_i(t) = y_i(\tau)$, it follows trivially from the inequality (18) that

$$r_i(t, \tau) \leq 0 \leq 2\lambda. \quad (21)$$

□

Remind that $\zeta_i(t)$ is a component of the variable $\zeta(t)$ depending on the bounded modeling uncertainties $w(t)$ and $v(t)$, as defined in (10). The boundedness of $w(t)$ and $v(t)$, together with Assumption 2, implies the boundedness of $\zeta(t)$. For practical convenience, the residual threshold should be directly derived from the assumed bounds of $w(t)$ and $v(t)$. It would require nontrivial error bound propagation through (10). Techniques of interval analysis or set-membership computation [12] can be applied for this purpose. This topic is not further discussed in this paper.

Proposition 1 guarantees the absence of false detection if fault detection is made by comparing the residual $r_i(t, \tau)$ with the threshold 2λ . However, it does not tell what are the faults which can be detected with such a decision rule. In general, robust fault detection methods are based on conservative decision rules, preventing the detection of some faults. In publications about robust fault detection, typically robustness results are provided, but the analysis about the set of faults which can be detected is usually absent, because it is often difficult to characterize the detectable faults in a robust detection framework. In contrast, for the method proposed in this paper, the faults which can be detected are clearly characterized as follows.

Proposition 2. *Assume that the system matrix pair (A, B) is controllable, $\theta \neq 0$, and $\theta_0 \neq 0$. For the faulty actuator parameter vector $\theta \neq \theta_0$, if there does not exist any positive real number α such that $\theta = \alpha\theta_0$, then there exist an input signal $u(t)$ and time instants t and τ such that*

$$r_i(t, \tau) > 2\lambda \quad (22)$$

for each $i = 1, \dots, m$, where λ is a positive constant such that $|\zeta_i(t)| \leq \lambda$.

Proof. This proof applies to the residual $r_i(t, \tau)$ for each $i = 1, \dots, m$.

Define the vector

$$v = \beta(\|\theta\|^{-1}\theta - \|\theta_0\|^{-1}\theta_0), \quad (23)$$

where the norm $\|\theta\| = \sqrt{\theta^T\theta}$ and β is a positive number to be specified later. Then

$$\begin{aligned} v^T\theta & = \beta(\|\theta\| - \|\theta_0\|^{-1}\theta_0^T\theta) \\ & = \beta\|\theta\|(1 - \|\theta_0\|^{-1}\|\theta\|^{-1}\theta_0^T\theta) \geq 0, \end{aligned} \quad (24)$$

where the last inequality follows from the fact that $|\theta_0^T\theta| \leq \|\theta_0\|\|\theta\|$.

Notice that the equality

$$|\theta_0^T\theta| = \|\theta_0\|\|\theta\| \quad (25)$$

would imply $\theta = \alpha\theta_0$ for some $\alpha > 0$, that is, the case excluded in Proposition 2. Therefore,

$$v^T\theta = \beta(\|\theta\| - \|\theta_0\|^{-1}\theta_0^T\theta) > 0. \quad (26)$$

Similarly, it is also shown that

$$v^T\theta_0 = \beta(\|\theta\| - \|\theta_0\|^{-1}\theta_0^T\theta) < 0. \quad (27)$$

It then follows that

$$\text{sign}[v^T\theta]v^T\theta_0 < 0. \quad (28)$$

For given values of θ and θ_0 , the value of β in (23) is chosen large enough such that

$$\begin{aligned} |v^T\theta| & > 2\lambda, \\ |v^T\theta_0| & > 2\lambda. \end{aligned} \quad (29)$$

Now, let us consider ϕ_i , the i th row of the matrix Φ defined in (9). If there is an input signal $u(t)$ such that $\phi_i(t) - \phi_i(\tau) = \nu^T$ for two time instants t and τ , then the inequality (28) leads to

$$\text{sign}[(\phi_i(t) - \phi_i(\tau))\theta](\phi_i(t) - \phi_i(\tau))\theta_0 < 0. \quad (30)$$

Notice that the existence of such input signals is ensured by the controllability of the matrix pair (A, B) .

Because $|(\phi_i(t) - \phi_i(\tau))\theta| = |\nu^T\theta| > 2\lambda \geq |\zeta_i(t) - \zeta_i(\tau)|$, the sign of $(\phi_i(t) - \phi_i(\tau))\theta + (\zeta_i(t) - \zeta_i(\tau))$ is determined by the sign of $(\phi_i(t) - \phi_i(\tau))\theta$, thus

$$\begin{aligned} \text{sign}[(\phi_i(t) - \phi_i(\tau))\theta + (\zeta_i(t) - \zeta_i(\tau))] \\ = \text{sign}[(\phi_i(t) - \phi_i(\tau))\theta]. \end{aligned} \quad (31)$$

This last equality, together with the inequality (30), leads to

$$\text{sign}[(\phi_i(t) - \phi_i(\tau))\theta + (\zeta_i(t) - \zeta_i(\tau))](\phi_i(t) - \phi_i(\tau))\theta_0 < 0, \quad (32)$$

or equivalently

$$\begin{aligned} \text{sign}[z_i(t) - z_i(\tau)](\phi_i(t) - \phi_i(\tau))\theta_0 < 0, \\ \text{sign}[y_i(t) - y_i(\tau)](\phi_i(t) - \phi_i(\tau))\theta_0 < 0. \end{aligned} \quad (33)$$

Remind that $|[\phi_i(t) - \phi_i(\tau)]\theta_0| = |\nu^T\theta_0| > 2\lambda$, then

$$\text{sign}[y_i(t) - y_i(\tau)][\phi_i(t) - \phi_i(\tau)]\theta_0 < -2\lambda. \quad (34)$$

Therefore, the residual as defined in (17) satisfies

$$r_i(t, \tau) > 2\lambda. \quad (35)$$

□

If t is the current time instant, then $r_i(t, \tau)$ can be computed for different past time instant τ . In order to reduce the effect of modeling uncertainties, $r_i(t, \tau)$ can be averaged over different values of τ in a sliding window. The computation of the residual from *sampled signals* is summarized as follows.

Residual generation algorithm summary

Assume that $\Phi(t)$ and $y(t)$ are sampled¹ at discrete time instants $1, 2, \dots, N$. Choose the sliding window length $0 < L < N$ for residual averaging. For each sensor number $i = 1, 2, \dots, m$, a residual is computed, for $k \geq L + 1$, through the formulas

$$\begin{aligned} r_i(k, s) &= -\text{sign}[y_i(k) - y_i(s)][\phi_i(k) - \phi_i(s)]\theta_0, \\ \bar{r}_i(k) &= \frac{1}{L} \sum_{s=k-L}^{k-1} \max(r_i(k, s), 0). \end{aligned} \quad (36)$$

Notice that the max function is used to exclude negative values of $r_i(k, s)$ in the computation of the average value.

4. FAULT ISOLATION

After the detection of an actuator fault, the purpose of fault isolation is to figure out which actuators are faulty. In terms of (11a) and (11b), it amounts to deciding which components of θ have deviated from the nominal value θ_0 .

It should be first remarked that, because of the arbitrary unknown function h , it is not possible to detect or isolate any proportional changes in all the components of θ . In other words, for any value $\alpha \in \mathbb{R}$, the parameter vector $\theta_1 = \alpha\theta_0$ cannot be distinguished from θ_0 based on the known signals $\Phi(t)$ and $y(t)$. For the same reason, if all the components of θ , except one, have changed, it is not possible to determine which one has not changed.

After having clarified the limitation related to unknown sensor distortion, let us look for an algorithm for fault isolation. The basic idea is to design residuals similar to (17), but capable of rejecting some actuator faults. Each designed residual should be insensitive to some of the possible actuator faults, whereas sensitive to the others. The actually occurred fault can then be isolated by comparing such residuals.

Let P be a permutation matrix, that is, a matrix obtained by permuting the rows of the $l \times l$ identity matrix I_l (remind that l is the number of actuators). Divide P into two submatrices P_f and P_s , respectively, composed of l_f and $l_s = l - l_f$ rows of P . Then it can be easily verified that

$$P_f^T P_f + P_s^T P_s = I_l. \quad (37)$$

The notations $P_f\theta$ and $P_s\theta$ will be used to select, respectively, the assumed *faulty* components and *sound* (or fault-free) components of θ . It is derived from (11a) that

$$z(t) = \Phi(t)P_f^T P_f\theta + \Phi(t)P_s^T P_s\theta + \zeta(t). \quad (38)$$

If P_s is assumed to select the components of θ corresponding to sound actuators, then, even after the occurrence of actuator faults, the equality

$$P_s\theta = P_s\theta_0 \quad (39)$$

still holds. Define

$$\theta_f \triangleq P_f\theta, \quad (40)$$

then

$$z(t) = \Phi(t)P_f^T\theta_f + \Phi(t)P_s^T P_s\theta_0 + \zeta(t). \quad (41)$$

For the purpose of fault isolation, different partitions of P into (P_f, P_s) should be considered. For each particular partition, a residual will be designed to be insensitive to changes in the corresponding subvector $\theta_f = P_f\theta$. Such a residual is said to be rejecting changes in θ_f . The rejection method used in the following is the estimation of θ_f from measure signals.

For two time instants t, τ , Assumption 1 implies (by rewriting inequality (15)) that

$$\begin{aligned} \text{sign}[y_i(t) - y_i(\tau)][(\phi_i(t) - \phi_i(\tau))P_f^T\theta_f + (\phi_i(t) - \phi_i(\tau)) \\ \times P_s^T P_s\theta_0 + \zeta_i(t) - \zeta_i(\tau)] \geq 0. \end{aligned} \quad (42)$$

¹ For notation simplicity, the sampling period is assumed to be 1 here.

For a given set of signals $\Phi(t)$, $y(t)$ sampled at discrete time instants $1, 2, \dots, N$, the value of θ_f can be estimated by minimizing the error term $\zeta_i(t) - \zeta_i(\tau)$ in the inequality (42) where the time instants t, τ are replaced by all pairs among the sampling instants $1, 2, \dots, N$.

Because $y_i(t) < y_i(s)$ and $y_i(s) < y_i(\tau)$ imply $y_i(t) < y_i(\tau)$, there would be too much redundancy if all the possible pairs among $1, 2, \dots, N$ were considered in (42). In order to reduce redundancy, for each sensor y_i , the data samples are sorted according to the values of $y_i(t)$, and only the neighboring pairs are considered. The algorithm is summarized as follows.

Residual generation algorithm summary

For each chosen partition of P into (P_f, P_s) , the residuals rejecting changes in $\theta_f = P_f\theta$ are computed as follows. For each sensor number $i = 1, 2, \dots, m$, sort the data such that

$$y_i(k_1^i) \leq y_i(k_2^i) \leq \dots \leq y_i(k_N^i). \quad (43)$$

Solve the constrained optimization problem

$$\min_{\theta_f} \max_{1 \leq i \leq m, 1 \leq j \leq N-1} \tilde{\zeta}_i(j), \quad (44)$$

subject to the constraints, for $i = 1, 2, \dots, m$ and $j = 1, 2, \dots, N-1$,

$$\begin{aligned} & [\phi_i(k_j^i) - \phi_i(k_{j+1}^i)] P_f^T \theta_f \\ & + [\phi_i(k_j^i) - \phi_i(k_{j+1}^i)] P_s^T P_s \theta_0 + \tilde{\zeta}_i(j) \leq 0. \end{aligned} \quad (45)$$

The corresponding sequences

$$\tilde{\zeta}_i(1), \tilde{\zeta}_i(2), \dots, \tilde{\zeta}_i(N-1), \quad i = 1, 2, \dots, m, \quad (46)$$

are the residuals rejecting changes in θ_f .

Remark that the inequality (45) corresponds to the inequality (42) where the omitted sign $[y_i(k_j^i) - y_i(k_{j+1}^i)]$ is always negative due to the sorted sequence, and accordingly, the inequality changes from “ \geq ” to “ \leq ”.

The constrained minimization (44)-(45) can be easily reformulated in the form of a standard linear programming problem. There are efficient numerical algorithms for its solution [13].

Proposition 3. *If the true parameter vector θ governing (11a) satisfies $P_s\theta = P_s\theta_0$, and if $|\zeta_i(t)| \leq \lambda$ for some constant λ and any t , then the residual $\tilde{\zeta}_i(j)$, solution of the constrained optimization problem (44)-(45), satisfies*

$$\tilde{\zeta}_i(j) \leq 2\lambda. \quad (47)$$

Proof. The proof of this result is quite straightforward. Let us first derive from (11a), (11b), and (37) that

$$\begin{aligned} & [\phi_i(k_j^i) - \phi_i(k_{j+1}^i)] P_f^T P_f \theta + [\phi_i(k_j^i) - \phi_i(k_{j+1}^i)] P_s^T P_s \theta \\ & + \zeta_i(k_j^i) - \zeta_i(k_{j+1}^i) = z_i(k_j^i) - z_i(k_{j+1}^i) \leq 0, \end{aligned} \quad (48)$$

where the indices k_j^i, k_{j+1}^i come from the sequence sorting $y_i(k)$ as in (43).

It is assumed that $P_s\theta = P_s\theta_0$. Then the above inequality shows that there exist a value of θ_f (equal to $P_f\theta$) and a value of $\tilde{\zeta}_i(j)$ (equal to $\zeta_i(k_j^i) - \zeta_i(k_{j+1}^i)$) such that the inequality (45) is satisfied. These values of θ_f and $\tilde{\zeta}_i(j)$ do not necessarily correspond to the solution of the constrained optimization problem (44)-(45), however, the optimal solution certainly has a value of $\tilde{\zeta}_i(j)$ not larger than $\zeta_i(k_j^i) - \zeta_i(k_{j+1}^i)$. Therefore,

$$\tilde{\zeta}_i(j) \leq \zeta_i(k_j^i) - \zeta_i(k_{j+1}^i) \leq 2\lambda. \quad (49) \quad \square$$

Property (47) has been proved under the assumption $P_s\theta = P_s\theta_0$. It can be shown that (47) holds also if $P_s\theta = \alpha P_s\theta_0$ for any $\alpha \in \mathbb{R}$ because of the unknown sensor distortion function.

For fault isolation, various matrices P_s are assumed and the corresponding residuals are computed. Then property (47) can be used to decide if each assumed P_s is correct or not. Alternatively, for different matrices P_s of the same size, the values of the residuals can also be compared for fault isolation.

Keep in mind that fault isolation cannot distinguish the cases such that $P_s\theta = \alpha P_s\theta_0$. For reliable fault isolation, the following assumption is required.

Assumption 3. There exists a permutation matrix P such that, for P_s composed of some rows of P ,

$$P_s\theta = P_s\theta_0, \quad (50)$$

and there does not exist any $\tilde{P}_s \neq P_s$ (except for \tilde{P}_s composed of a subset of permuted rows of P_s) such that

$$\tilde{P}_s\theta = \alpha \tilde{P}_s\theta_0, \quad (51)$$

for some scalar real value α .

5. NUMERICAL EXAMPLE

In this section, the presented fault diagnosis method will be illustrated with a simulated distillation column.

In [14, page 223], a distillation column is modeled with a transfer function matrix with three control inputs: top draw flow rate, side draw flow rate, and bottom temperature control, and three outputs: top draw composition, side draw composition, and bottom reflux temperature. In order to illustrate the possibility of fault diagnosis with only one output sensor, let us consider the model relating the three inputs and one of the outputs, the bottom reflux temperature. The transfer function model is

$$Z(s) = \frac{4.38e^{-20s}}{33s+1} U_1(s) + \frac{4.42e^{-22s}}{44s+1} U_2(s) + \frac{7.20}{19s+1} U_3(s). \quad (52)$$

Note that the known time delays at the inputs do not cause any serious difficulty for fault diagnosis, though the on-line computation has to be delayed accordingly.

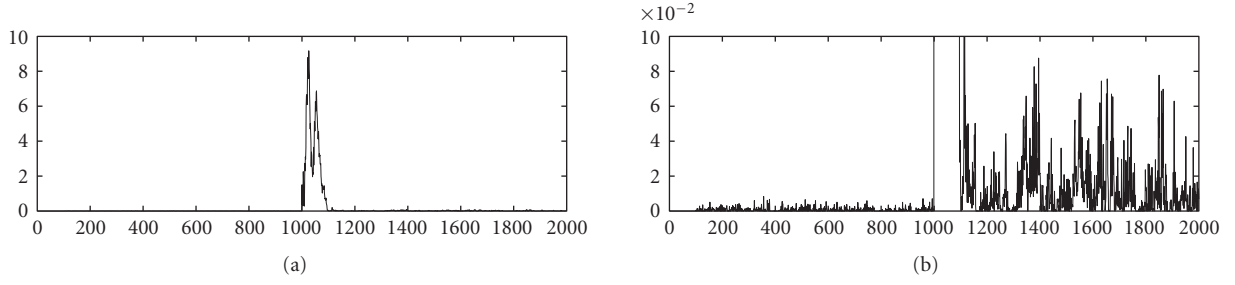


FIGURE 1: Fault detection residual. The same residual is plotted twice at different scales. The time unit is the minute.

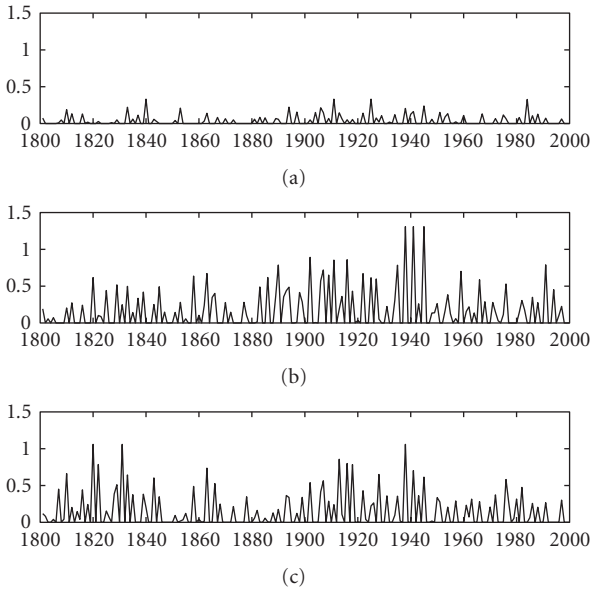


FIGURE 2: Fault isolation residuals. The time unit is the minute. Top: residual rejecting the fault of actuator 1. Middle: residual rejecting the fault of actuator 2. Bottom: residual rejecting the fault of actuator 3.

Numerical simulation is first made in continuous time. The three input variables are randomly drawn with uniform distributions ranged within the intervals $[20, 40]$ (mol/min), $[10, 30]$ (mol/min) and $[10, 20]$ ($^{\circ}\text{C}$). The simulated noise-free output is disturbed by an additive bandlimited noise with noise power 0.01 and unitary sample time. Then the sensor distortion function

$$h(z) = \frac{100}{1 + e^{-0.2(z-320)}} + 10 \quad (53)$$

is applied. In this monotonously increasing function, the additive constant 10 has been added to illustrate the robustness of the proposed method to sensor bias (shifting error). Finally, the distorted sensor output $y(t)$ sampled at the period of one minute is corrupted by a random noise uniformly distributed within the interval $[-0.05, 0.05]$ ($^{\circ}\text{C}$). The simulated data is recorded during 2000 minutes after an initial simulation of 1000 minutes to avoid the initial transient pe-

riod. At the beginning, all the actuators are fault free. At the 1000th minute (of the recorded duration), a factor of 0.8 is applied to the first actuator, simulating an actuator fault.

The residual for fault detection, computed with the averaging window length $L = 100$, is illustrated in Figure 1. In Figure 1(a) showing the residual in full scale, there is a strong transient behavior of the residual after occurrence of the actuator fault (at the 1000th minute). This transient behavior is in favor of a fast detection of the actuator fault. In order to view better the residual outside the transient period, it is plotted in Figure 1(b) in a finer scale. The detected fault is clearly confirmed by the residual after the transient period.

For fault isolation, three residuals are computed with the signals from the 1801th minute to the 2000th minute. Each of the three residuals is designed to reject a fault affecting one of the three actuators. The residuals rejecting the faults of actuator 1, 2, and 3 are, respectively, plotted in the top, middle, and bottom pictures of Figure 2. The first residual is clearly smaller than the two others, indicating that the hypothesis of a fault affecting the first actuator is the most likely one, which corresponds to the actually simulated fault.

6. CONCLUSION

Despite unknown nonlinear distortions of sensors, the information provided by such sensors is still useful for fault diagnosis, even when there is no redundant sensors, if the distortions are strictly monotonous. The monotonousness is a weak assumption since nonmonotonous distortion would make the sensor information useless. The main idea of the method presented in this paper is about how to use the information provided by such sensors. Because of the unknown nature of nonlinear distortion, neither the absolute value of the measured physical variable nor its sign can be determined from the sensor signal. The strict monotonousness of the nonlinear distortion is not helpful in this aspect. However, for any two different time instants, the relative sign of the measured variable is preserved by the monotonous nonlinear distortion. By using the information residing in the relative sign of sensor signals, the method for actuator fault diagnosis presented in this paper is conceptually robust to sensor distortions, as illustrated by the numerical example presented in this paper.

REFERENCES

- [1] M. Basseville and I. Nikiforov, *Detection of Abrupt Changes: Theory and Applications*, Information and System Sciences Series, Prentice-Hall, Englewood Cliffs, NJ, USA, 1993.
- [2] J. J. Gertler, *Fault Detection and Diagnosis in Engineering Systems*, Marcel Dekker, New York, NY, USA, 1998.
- [3] J. Chen and R. J. Patton, *Robust Model-Based Fault Diagnosis for Dynamic Systems*, Kluwer Academic Publishers, Dordrecht, The Netherlands, 1999.
- [4] M.-A. Massoumnia, G. C. Verghese, and A. S. Willsky, "Failure detection and identification," *IEEE Transactions on Automatic Control*, vol. 34, no. 3, pp. 316–321, 1989.
- [5] C. De Persis and A. Isidori, "A geometric approach to nonlinear fault detection and isolation," *IEEE Transactions on Automatic Control*, vol. 46, no. 6, pp. 853–865, 2001.
- [6] P. W. Tse, W.-X. Yang, and H. Y. Tam, "Machine fault diagnosis through an effective exact wavelet analysis," *Journal of Sound and Vibration*, vol. 277, no. 4-5, pp. 1005–1024, 2004.
- [7] H. Ma, C. Han, X. Kong, G. Wang, J. Xu, and X. Zhu, "A chaos-GFRF based fault diagnosis method," in *Proceedings of IEEE Conference on Cybernetics and Intelligent Systems (ICCI '04)*, vol. 2, pp. 1314–1317, Singapore, December 2004.
- [8] K. Kumamaru, K. Inoue, and T. Iwamura, "Improved approach to KDI-based fault detection for non-linear black-box systems," in *Proceedings of the SICE Annual Conference*, vol. 1, pp. 927–932, Sapporo, Japan, August 2004.
- [9] M. E. H. Benbouzid, H. Nejjari, R. Beguenane, and M. Vieira, "Induction motor asymmetrical faults detection using advanced signal processing techniques," *IEEE Transactions on Energy Conversion*, vol. 14, no. 2, pp. 147–152, 1999.
- [10] Q. Zhang, "A method for actuator fault diagnosis with robustness to sensor distortion," in *Proceedings of the 6th IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes (SAFEPROCESS '06)*, Beijing, China, August–September 2006.
- [11] Q. Zhang, A. Iouditski, and L. Ljung, "Identification of Wiener system with monotonous nonlinearity," in *Proceedings of IFAC Symposium on System Identification*, Newcastle, Australia, March 2006.
- [12] R. B. Kearfott and V. Kreinovich, Eds., *Applications of Interval Computations*, Kluwer Academic Publishers, Boston, Mass, USA, 1996.
- [13] D. Den Hertog, *Interior point approach to linear, quadratic, and convex programming: algorithms and complexity*, Kluwer Academic Publishers, Dordrecht, The Netherlands, 1994.
- [14] T. Glad and L. Ljung, *Control Theory: Multivariable and Non-linear Methods*, Taylor & Francis, New York, NY, USA, 2000.

Special Issue on Machine Learning Paradigms for Modeling Spatial and Temporal Information in Multimedia Data Mining

Call for Papers

Multimedia data mining and knowledge discovery is a fast emerging interdisciplinary applied research area. There is tremendous potential for effective use of multimedia data mining (MDM) through *intelligent* analysis. Diverse application areas are increasingly relying on multimedia understanding systems. Advances in multimedia understanding are related directly to advances in signal processing, computer vision, machine learning, pattern recognition, multimedia databases, and smart sensors.

The main mission of this special issue is to identify state-of-the-art machine learning paradigms that are particularly powerful and effective for modeling and combining temporal and spatial media cues such as audio, visual, and face information and for accomplishing tasks of multimedia data mining and knowledge discovery. These models should be able to bridge the gap between low-level audiovisual features which require signal processing and high-level semantics. Original contributions, not currently under review or accepted by another journal, are solicited in relevant areas including (but not limited to) the following:

- Multiresolution-based video mining and features extraction
- Dimension reduction and unsupervised data clustering for multimedia content analysis tasks
- Mining methods and algorithms (classification, regression, clustering, probabilistic modelling), as well as association analysis
- Machine learning paradigms that perform spatial and temporal data mining
- Machine learning paradigms that allow for an effective learning of hidden patterns
- Object recognition and tracking using machine learning algorithms
- Interactive data exploration and machine learning discovery
- Mining of structured, textual, multimedia, spatiotemporal, and web data
- Application of MDM to contents-based image/video retrieval and medical data

Before submission authors should carefully read over the journal's Author Guidelines, which are located at <http://www.hindawi.com/journals/aai/guidelines.html>. Prospective authors should submit an electronic copy of their complete manuscript through the journal Manuscript Tracking System at <http://mts.hindawi.com/> according to the following timetable:

| | |
|------------------------|-----------------|
| Manuscript Due | October 1, 2009 |
| First Round of Reviews | January 1, 2010 |
| Publication Date | April 1, 2010 |

Lead Guest Editor

Djamel Bouchaffra, Grambling State University, Grambling, LA, USA; dbouchaffra@ieee.org

Guest Editors

Ce Zhu, Nanyang Technological University, Singapore; eczhu@ntu.edu.sg

Abbes Amira, Brunel University, Uxbridge, Middlesex, UK; abbes.amira@brunel.ac.uk

Chu-Song Chen, Institute of Information Science, Taipei, Taiwan; song@iis.sinica.edu.tw

Special Issue on Fuzzy Logic Techniques for Clean Environment

Call for Papers

The fuzzy technique for clean energy, solar and wind energy, is the most readily available source of energy, and one of the important sources of the renewable energy, because it is nonpolluting and, therefore, helps in lessening the greenhouse effect. The benefits arising from the utilization of solar and wind energy systems can be categorized into two sections: energy saving and the decrease of environmental pollution. The clean energy saving benefits come from the reduction in electricity consumption and from using any conventional energy supplier, which can avoid the expenditure of fuel supply. The other main benefit of the renewable energy is the decrease of environmental pollution, which can be achieved by the reduction of emissions due to the usage of electricity and conventional power stations. Electricity production using solar and wind energy is of the main research areas at present in the field of renewable energies, the significant price fluctuations are seen for the fossil fuel in one hand, and the trend toward privatization that dominates the power markets these days in the other hand, will drive the demand for solar technologies in the near term. The process of solar distillation is used worldwide for arid communities that do not have access to potable water. Also some solar technologies provide other benefits beside power generation, that is, fresh water (using desalination techniques).

The main focus of this special issue will be on the applications of fuzzy techniques for clean energy. We are particularly interested in manuscripts that report the fuzzy techniques applications of clean energy (solar, wind, desalination, etc.). Potential topics include, but are not limited to:

- Solar power station
- Wind power
- Photovoltaic and renewable energy engineering
- Renewable energy commercialization
- Solar cities
- Solar powered desalination unit
- Solar power
- Solar power plants
- Solar systems (company)
- World solar challenge

- Seawater desalination to produce fresh water
- Desalination for long-term water security

Before submission authors should carefully read over the journal's Author Guidelines, which are located at <http://www.hindawi.com/journals/afs/guidelines.html>. Prospective authors should submit an electronic copy of their complete manuscript through the journal Manuscript Tracking System at <http://mts.hindawi.com/>, according to the following timetable:

| | |
|------------------------|-----------------|
| Manuscript Due | October 1, 2009 |
| First Round of Reviews | January 1, 2010 |
| Publication Date | April 1, 2010 |

Guest Editors

Rustom M. Mamlook, Middle East University for Graduate Studies, Amman, Jordan; rstmamlk@hotmail.com

Guest Editors

S. Paramasivam, ESAB Engineering Services Limited, Tamil Nadu 600 058, India; param@ieee.org

Mohammad Ameen Al-Jarrah, American University of Sharjah, P.O. Box 26666, Sharjah, UAE; mjarrah@aus.edu

Zeki Ayag, Kadir Has University, 34083 Istanbul, Turkey; zekia@khas.edu.tr

Ashok B. Kulkarni, University of Technology, Kingston 6, Jamaica; kulkarniab2@rediffmail.com

Special Issue on Selected Papers from Workshop on Synergies in Communications and Localization (SyCoLo 2009)

Call for Papers

In conjunction with the IEEE International Conference on Communications (ICC) 2009 in Dresden, Germany, the International Workshop on Synergies in Communications and Localization (SyCoLo 2009) will be held.

The main objective of this workshop is to show how wireless communications and navigation/localization techniques can benefit from each other. With respect to these synergies the workshop aims at the following fundamental questions:

- How can navigation systems benefit from existing communications systems?
- How can communication systems benefit from positioning information of mobile terminals?

This workshop, whose proposal was jointly generated by the EU Research Projects WHERE and NEWCOM++, aims at inspiring the development of new position-aware procedures to enhance the efficiency of communication networks, and of new positioning algorithms based both on (outdoor or indoor) wireless communications and on satellite navigation systems.

The SyCoLo 2009 is, therefore, well in agreement with the new IJNO journal aims at promoting and diffusing the aims of joint communications and navigation among universities, research institutions, and industries.

This proposed IJNO Special Issue focuses all the research themes related to the timing aspects of joint communications and navigation, and starts from the SyCoLo 2009 where the Guest Editors will attend the different sessions and directly invite the authors of the most promising papers to submit an extended version of their papers to the journal.

The proposed Guest Editors are also part of the Scientific Committees of the SyCoLo 2009, therefore, directly involved in the evaluation of submitted papers.

Topics of interest will include, but are not limited to:

- Hybrid positioning using both wireless communications and satellite navigation systems
- Resource management with positioning information
- Location-aware PHY/MAC algorithms/procedures

- Indoor positioning combined with short-range communications
- Signal processing techniques for (seamless) indoor/outdoor localization

Before submission authors should carefully read over the journal's Author Guidelines, which are located at <http://www.hindawi.com/journals/ijno/guidelines.html>. Prospective authors should submit an electronic copy of their complete manuscript through the journal Manuscript Tracking System at <http://mts.hindawi.com/> according to the following timetable:

| | |
|------------------------|-----------------|
| Manuscript Due | October 1, 2009 |
| First Round of Reviews | January 1, 2010 |
| Publication Date | April 1, 2010 |

Lead Guest Editor

Ronald Raulefs, German Aerospace Center (DLR), Institute of Communications and Navigation, Oberpfaffenhofen, Wessling 82234, Germany; ronald.raulefs@dlr.de

Guest Editors

Simon Plass, Institute of Communications and Navigation, German Aerospace Center (DLR), 82234 Wessling, Germany; simon.plass@dlr.de

Marco Luise, Dipartimento di Ingegneria dell'Informazione, Università di Pisa, Via G. Caruso 16, 56126 Pisa, Italy; marco.luise@iet.unipi.it