CONTROL OF AN UNCERTAIN THREE-TANK SYSTEM VIA ON-LINE PARAMETER IDENTIFICATION AND FAULT DETECTION

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Abstract:
We provide fast and on-line methods for failure detection and isolation of uncertain nonlinear systems which are operating in closed-loop. They are based on accurate values of the derivatives of a time-signal, which are obtained via new algebraic estimation techniques. The applicability and efficiency of our approach are illustrated by numerical simulations for a most popular case-study, namely the three-tank system.

Keywords: Fault detection and isolation, residuals, estimation of time derivatives, parameter estimation, flat nonlinear systems.

1. INTRODUCTION

Failure detection and isolation (FDI) has undergone considerable development in recent years leading to a wide variety of model-based approaches (Frank, 1990; Staroswiecki and Comtet-Varga, 2001). According to the deviation between measurements (inputs and the output variables) and corresponding model-based computations, *fault indicators* or *residues* are generated. One of the most attractive methodologies developed so far, for failure detection, is known as the *Fundamental Problem of Residual Generation* (FPRG) introduced in (Jones, 1973; Willsky, 1976) and more recently treated in (White and Speyer, 1987; Massoumnia, 1989). The main idea is to make each generated residual sensitive only to a single fault thus ensuring fault isolation in the case of multiple faults. Other approaches are based on nonlinear models and were developed to extend the domain of FDI applications as in (Chen, 1999; De Persis and Isidori, 2001; Gertler, 1998; Join, 2002; Join *et al.*, 2003).
Based on our previously developed results (Fliess *et al.*, 2004b; Fliess *et al.*, 2005a) for on-line fault detection and isolation, we propose in this

communication a new method for on-line FDI in the context of a specific nonlinear multivariable system. We undertake, as a case study, the well known three-tank system, subject to actuator and sensor failures, with poorly known physical parameters. Although the process may not represent a full production-type industrial plant, it exhibits characteristics which are common in real life (nonlinearities, multiple inputs, multiple outputs, noisy measurements, etc).

Several fault diagnosis methods have been proposed for systems linearized around an operating equilibrium point (see, for instance, (Koenig *et al.*, 1997; Akhenak *et al.*, 2003; Zhou and Frank, 1999; Theilliol *et al.*, 2002)). Some of these techniques have also been extended to the case of nonlinear systems. In (Shields and Du, 2000) nonlinear observers are synthesized to detect tank leakage. In (Koscielny, 1999) a method is proposed for fault diagnosis using techniques stemming from *fuzzy sets.* In (Zolghadri *et al.*, 1996) an alternative is developed to detect leaks in uncertain tank systems. Experimental results on sensor fault tolerant control have been reported in (Zhou *et al.*, 2000).

In this paper, *fault indicators* or *residues* are synthesized which are robust with respect to uncertain parameters in the controlled plant and which effectively act while the system is operating in closed loop conditions. Our techniques involve the efficient computation of time derivatives of measured system inputs and outputs[1]. Under a reasonable hypothesis of delayed failures, we use algebraic based methods to online identify the unknown constant system parameters. The gathered knowledge of the parameters allow us to implement our residue generation techniques for on-line fault detection and isolation. Note that, in this nonlinear uncertain context, the problem of combined fault detection and isolation has received, to the best of our knowledge, no attention.

Our paper is organized as follows: The problem statement is presented in section 2. The basics of our approach are given in section 3. Section 4 is devoted to the concrete case-study of the three-tank-system with an unknown parameter. We provide some convincing computer simulation results for failure residual generation which are characterized by the following facts:

- isolation of actuator faults,
- fast performance in on-line closed loop operation,
- insensitivity to parameter uncertainties and other classical perturbations,
- robustness with respect to additive measurement and plant noises.

[1] Compare with (Diop and Martinez-Guerra, 2001).

Some directions for future work are listed in the conclusions of the article.

2. PROBLEM STATEMENT

Consider a system of the form

$$\begin{cases} \dot{x} = f(t, x, u, \Theta, w) \\ y = h(t, x, u, \Theta, w) + \pi \end{cases}$$

where

- the vector-valued functions f and h may be nonlinear;
- $x = (x_1, \ldots, x_n)$, $u = (u_1, \ldots, u_m)$ and $y = (y_1, \ldots, y_p)$ denote respectively the state, control and output variables;
- Θ is a finite set of unknown parameters;
- w is a finite set of fault variables;
- π is a finite set of perturbations variables, which are assumed here to be high frequency noises.

The fundamental problem of fault detection and isolation lies in the generation of indication signals, usually called *residuals*, which point to the sudden appearance of a fault. Any fault variable w_i, which is *isolable*, may be written (see, *e.g.*, (Fliess *et al.*, 2005a; Fliess *et al.*, 2005b)):

$$w_i = g(t, y, \dot{y}, \cdots, y^{(j)}, u, \dot{u}, \cdots, u^{(k)}, \Theta)$$

where g is a nonlinear function of its arguments. Uncertain parameters play a crucial rôle. It is moreover often difficult to distinguish the effect of a fault from the contributions of uncertain parameters and other perturbations. We propose here to carry out a suitable combination of parameter estimation and residual generation. To this purpose, we assume, based on the fast nature of our methods, that only a short time interval is dedicated to the computations leading to parameter estimations. Naturally, it is assumed that faults do not occur during this short interval of time. Lastly, to prevent the amplification of high frequency noises, a special method, based also on algebraic results, is used to estimate the successive time derivatives of input and output signals. A residual r_i corresponding to w_i may then be written:

$$r_i = g(t, y, \cdots, [y^{(j)}]_e, u, \cdots, [u^{(k)}]_e, [\Theta]_e) \quad (1)$$

where

- $[\Theta]_e$ is the vector of parameter estimations,
- $[u^{(k)}]_e$ and $[y^{(j)}]_e$ are the on-line estimations of input and output time derivatives.

The next section explains the conditions under which the proposed method is applicable.

3. PARAMETER ESTIMATION AND FAULT DIAGNOSIS

Using techniques stemming from differential algebra and by resorting to the procedures introduced in (Fliess and Sira-Ramírez, 2004c) for the estimation of time derivatives of measured signals [2], our method allows to obtain efficient and easily computable parameter estimation and residuals.

Remark 3.1. Note that the connections of differential algebra with computer algebra have already been exploited in nonlinear fault diagnosis by (Zhang, et al., 1998; Staroswiecki and Comtet-Varga, 2001; Diop and Martinez-Guerra, 2001).

3.1 Estimation of the derivatives

Consider a real-valued time function $x(t)$ which is assumed to be analytic on some interval $t_1 \leq t \leq t_2$. Assume for the sake of simplicity that $x(t)$ is analytic around $t = 0$ and introduce its truncated Taylor expansion

$$x(t) = \sum_{\nu=0}^{N} x^{(\nu)}(0)\frac{t^\nu}{\nu!} + O(t^{\nu+1})$$

Approximate $x(t)$ in the interval $(0, \varepsilon)$, $\varepsilon > 0$, by a polynomial $x_N(t) = \sum_{\nu=0}^{N} x^{(\nu)}(0)\frac{t^\nu}{\nu!}$ of degree N. The usual rules of symbolic calculus in Schwartz's distributions theory (Schwartz, 1966) yield

$$x_N^{(N+1)}(t) = x(0)\delta^{(N)} + \dot{x}(0)\delta^{(N-1)} + \cdots + x^{(N)}(0)\delta$$

where δ is the Dirac measure at 0. From $t\delta = 0$, $t\delta^{(\alpha)} = -\alpha\delta^{(\alpha-1)}$, $\alpha \geq 1$, we obtain the following triangular system of linear equations for determining estimated values $[x^{(\nu)}(0)]_e$ of the derivatives [3] $x^{(\nu)}(0)$:

$$\begin{aligned} t^\alpha x^{(N+1)}(t) = t^\alpha \Big(& [x(0)]_e\delta^{(N)} + [\dot{x}(0)]_e\delta^{(N-1)} \\ & + \cdots + [x^{(N)}(0)]_e\delta \Big) \end{aligned} \tag{2}$$

$$\alpha = 0, \ldots, N$$

The time derivatives of $x(t)$ and the Dirac measures and its derivatives are removed by integrating with respect to time both sides of equation (2) at least N times:

$$\begin{aligned} \int^{(\nu)} \tau_1^\alpha x^{(N+1)}(\tau_1) = \int^{(\nu)} & \tau_1^\alpha \Big([x(0)]_e\delta^{(N)} \\ & + [\dot{x}(0)]_e\delta^{(N-1)} + \ldots \\ & + [x^{(N)}(0)]_e\delta \Big) \end{aligned} \tag{3}$$

$$\nu \geq N, \ \alpha = 0, \ldots, N$$

where $\int^{(\nu)} = \int_0^t \int_0^{\tau_{\nu-1}} \ldots \int_0^{\tau_1}$. A quite accurate value of the estimates may be obtained with a small time window $[0, t]$. Only valid after a small time interval, in practice, the derivative estimations need to be reset when the validity of the approximation becomes questionable. Discussions on *calculation resettings* are given in (Sira-Ramírez and Fliess, 2004).

Moreover the iterated integrals are low pass filters. They are attenuating high frequency noises, which are usually dealt with in a statistical setting (see (Fliess *et al.*, 2003b) for more details).

3.2 Parameter estimations

Parameter estimations are carried out using an extension of the algebraic methods introduced for linear systems in (Fliess and Sira-Ramírez, 2003a). In this method only a short interval of time is required to accurately accomplish parameter estimations. Nevertheless, we assume that during this short time interval the system operates in a *fault free* manner. We thus consider that the condition $w = 0$ is valid in an open time interval. For the sake of simplicity, we assume that this time interval exists at the beginning of the operation of the system.

Assume that the unknown parameters $\Theta = (\theta_1, \cdots, \theta_r)$ satisfy some natural *algebraic identifiability* conditions (Diop and Fliess, 1991a; Diop and Fliess, 1991b). Then, for $\iota = 1, \cdots, r$,

$$\theta_\iota = \Upsilon_\iota(t, y, \cdots, y^{(j)}, u, \cdots, u^{(k)}) \tag{4}$$

where Υ_ι is a nonlinear function of its arguments. An accurate estimate $[\theta_\iota]_e$ of θ_ι is obtained by replacing in equation (4) the derivatives of the control and output variables by their estimated values:

$$[\theta_\iota]_e = \Upsilon_\iota(t, y, \cdots, [y^{(j)}]_e, u, \cdots, [u^{(k)}]_e)$$

3.3 Fault diagnosis

Equation (1) demonstrates that an excellent fault indicator may be obtained in the same way, *i.e.*, via accurate estimates of the derivatives of the control and output variables, which provide moreover estimates of the unknown parameters.

4. APPLICATION TO THE THREE-TANK-SYSTEM

4.1 Process description

The three tank system model depicted in figure 1 is written using the well known "mass balance"

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[2] Compare with the recent study (Moussaoui, Brie *et al.*, 2005) via analytic methods. It might be appropriate here to recall that the reference (Fliess and Sira-Ramírez, 2003a) contains to the best of our knowledge perhaps the first closed-loop identification scheme for continuous-time linear systems, which has already been validated by numerous concrete case-studies.

[3] Those quantities are *linearly identifiable* (see (Fliess and Sira-Ramírez, 2003a) and (Fliess *et al.*, 2004a)).

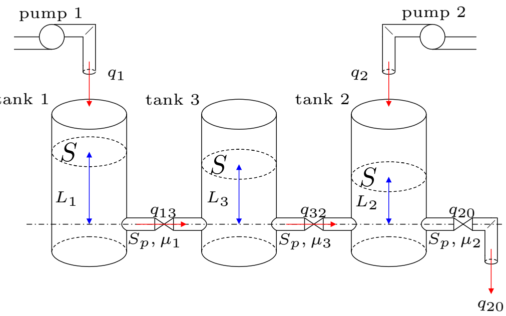

Fig. 1. The three-tank-system

equations. The system can be conveniently represented as in (AMIRA, 1996) by

$$\begin{cases} S\frac{dL_1}{dt} = q_1 - q_{13} \\ S\frac{dL_2}{dt} = q_2 + q_{32} - q_{20} \\ S\frac{dL_3}{dt} = q_{13} - q_{32} \end{cases}$$

where q_{ij} represents the water flow rate from tank i to j, $i, j = 1, 2, 3$, which, according to Torricelli's rule is given by

$$q_{ij} = \mu_i.S_p.\text{sign}(L_i - L_j).\sqrt{2g|L_i - L_j|}$$

Notice that q_{20} represents the outflow rate with

$$q_{20} = \mu_2.S_p.\sqrt{2gL_2}$$

The full system model is then obtained as follows

$$\begin{cases} \dot{x}_1 = & -C_1\text{sign}(x_1 - x_3)\sqrt{|x_1 - x_3} \\ & +(u_1 + w_1)/S \\ \dot{x}_2 = & C_3\text{sign}(x_3 - x_2)\sqrt{|x_3 - x_2|} \\ & -C_2\text{sign}(x_2)\sqrt{|x_2|} \\ & +(u_2 + w_2)/S \\ \dot{x}_3 = & C_1\text{sign}(x_1 - x_3)\sqrt{|x_1 - x_3|} \\ & -C_3\text{sign}(x_3 - x_2)\sqrt{|x_3 - x_2|} \\ y_1 = & x_1 \\ y_2 = & x_2 \\ y_3 = & x_3 \end{cases}$$

where $x_i(t)$ is the liquid level in tank i and $C_i = (1/S).\mu_i.S_p.\sqrt{2g}$. The two control signals $u_1(t)$, $u_2(t)$ are, respectively, the input flow $q_1(t)$ and $q_2(t)$. We assume the possible existence of actuator faults, denoted by w_1 and w_2, which perturb the behavior of the system. These actuator faults must be *detected* and *isolated*. We additionally assume that the model of the system is not exactly known. Indeed, the output flow coefficients μ_i are regarded as uncertain constant coefficients.

4.2 Control

The system, although non-differentiable, may be regarded as a *flat hybrid* system[4]. Indeed, the system has four possible *state locations*. In each location a differentiable model is obtained. The state space regions corresponding to such locations are $x_1 \geq x_3$ or $x_1 < x_3$ and $x_2 \geq x_3$ or $x_2 < x_3$, the resulting models are all flat with flat outputs given by x_1 and x_3.

Synthesizing the four possible control input parametrization, in terms of $x_1^* = F_1$ and $x_3^* = F_3$, into a unique expression, we may obtain the following nominal open loop control

$$u_1^* = S\Big(\dot{F}_1 + C_1\text{sign}(F_1 - F_3)\sqrt{F_1 - F_3}\Big)$$

and

$$\begin{aligned} u_2^* = \ & S\Big(\dot{x}_2^* - C_3\text{sign}(F_3 - x_2^*)\sqrt{|F_3 - x_2^*|} \\ & +C_2\text{sign}(x_2^*)\sqrt{|x_2^*|}\Big) \end{aligned}$$

where

$$\begin{aligned} x_2^* = \ & \varepsilon F_3 \\ & -\varepsilon\left(\frac{-\dot{F}_2 + C_1\text{sign}(F_1 - F_3)\sqrt{|F_1 - F_3|}}{C_3}\right)^2 \end{aligned}$$

and

$$\varepsilon = \begin{cases} +1 \text{ if } F_3 > x_2^* \\ -1 \text{ if } F_3 < x_2^* \end{cases}$$

The loop is closed via a nonlinear extension (see, also, (Hagenmeyer and Delaleau, 2003a; Hagenmeyer and Delaleau, 2003b)) of the classic PI controller:

$$\begin{aligned} u_1 = \ & u_1^* + SC_1\text{sign}(y_1 - y_3)\sqrt{|y_1 - y_3|} \\ & -SC_1\text{sign}(F_1 - F_3)\sqrt{|F_1 - F_3|} \\ & -P_1Se_1 - P_2S\int e_1 \end{aligned}$$

$$\begin{aligned} u_2 = \ & u_2^* - SC_3\text{sign}(y_3 - y_2)\sqrt{|y_3 - y_2|} + SC_2\sqrt{|y_2|} \\ & +SC_3\text{sign}(F_3 - x_2^*)\sqrt{|F_3 - x_2^*|} - SC_2\sqrt{|x_2^*|} \\ & -P_3Se_3 - P_4S\int e_3 \end{aligned}$$

where $e_i = y_i - F_i^*$ is the tracking error. For the gain coefficients set $P_1 = P_3 = 2.10^{-2}$, $P_2 = P_4 = 2.10^{-4}$.

4.3 Fault diagnosis

We use the method of section 3.1 to estimate the first time derivatives of the output $[\dot{y}_i]_e$.

4.3.1. Estimation of uncertain coefficients The unknown outflow coefficients are estimated via

$$[\mu_1]_e = \frac{-(S[\dot{y}_1]_e - u_1)}{S_p\text{sign}(y_1 - y_3)\sqrt{2g|y_1 - y_3|}}$$
$$[\mu_2]_e = \frac{-(S[\dot{y}_1]_e + S[\dot{y}_2]_e + S[\dot{y}_3]_e - u_1 - u_2)}{S_p\text{sign}(y_2)\sqrt{|y_2|}}$$
$$[\mu_3]_e = \frac{-(S[\dot{y}_1]_e + S[\dot{y}_3]_e - u_1)}{S_p\text{sign}(y_3 - y_2)\sqrt{2g|y_3 - y_2|}}$$

After a short period of time has elapsed, the previous estimates of the constant values of the

[4] For an excellent overview of flatness (Fliess *et al.*, 1995), see the recent book by (Sira-Ramírez and Agrawal, 2004).

μ's become available for the implementation of our control and detection schemes.

4.3.2. Fault diagnosis The fault variables are estimated via the following equations

$$\begin{aligned}[w_1]_e &= S[\dot{y}_1]_e \\ &\quad +[\mu_1]_c S_p \mathrm{sign}(y_1 - y_3)\sqrt{2g|y_1 - y_3|} \\ &\quad -u_1 \\ [w_2]_e &= S[\dot{y}_2]_e \\ &\quad -[\mu_3]_c S_p \mathrm{sign}(y_3 - y_2)\sqrt{2g|y_3 - y_2|} \\ &\quad +[\mu_2]_c S_p \mathrm{sign}(y_2)\sqrt{2g|y_2|} - u_2\end{aligned}$$

Thus residuals ensuring faults diagnosis are $r_1 = [w_1]_e$ and $r_2 = [w_2]_e$.

4.4 Simulation results

The known system parameters are:

$$\begin{cases} S = 0.0154m \\ Sp = 5.10^{-5}m \\ g = 9.81m.s^{-2} \end{cases}$$

The nominal values of the parameters $\mu_1 = \mu_3 = 0.5$, $\mu_2 = 0.675$ are used only to compute the nominal references trajectories.
The system behavior, both in the fault free case and in the faulty case can be compared from figure 2. Estimations of the outflow are presented in figure 3. The real coefficients, obtained from our computations, are naturally slightly different from the nominal coefficients:

$$\begin{aligned}[\mu_1]_{real} &= \mu_1 * (1 + 0.33) \\ [\mu_2]_{real} &= \mu_2 * (1 - 0.33) \\ [\mu_3]_{real} &= \mu_3\end{aligned}$$

At time $t = 500T_e$[5] , the last estimations of those coefficients are utilized for residual synthesis

$$\begin{aligned}[\mu_1]_c &= 0.6836 \\ [\mu_2]_c &= 0.4339 \\ [\mu_3]_c &= 0.4819\end{aligned}$$

As shown in figure 4, fault occurrence and its corresponding discrimination is easily realized. Note that the behavior of residuals at time $t = 500T_e$ is changing: this is due to the fact that the nominal value of μ_i is being used before $t = 500T_e$.

5. CONCLUSION

We were able, thanks to our approach, to determine robust residuals for fault diagnosis, which are working in closed loop and are valid for uncertain nonlinear systems. Those methods, which are also important in signal processing (Fliess *et al.*, 2004a), will be essential for building a general theory of fault tolerant control (see (Fliess *et al.*, 2005b) for a preliminary study).

[5] T_e denotes the sampling period.

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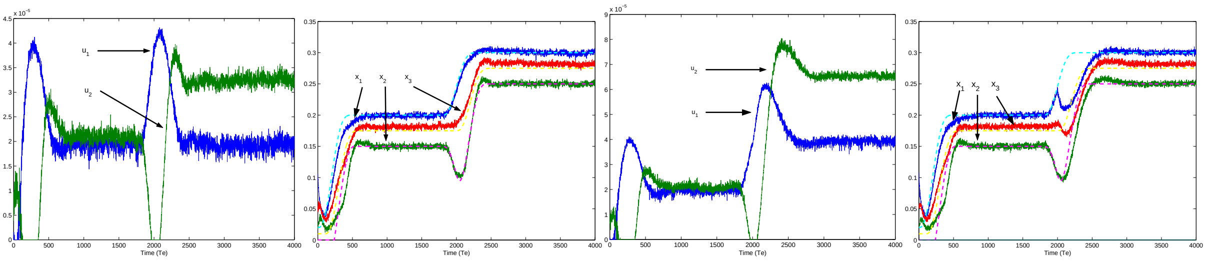
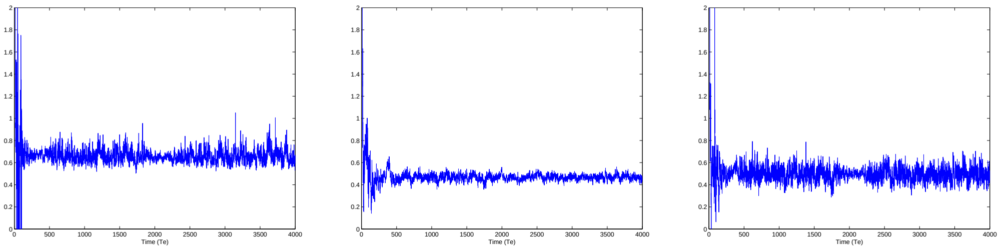


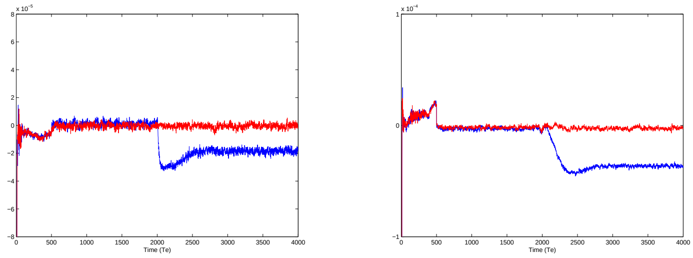
(a) Control inputs *(b)* Measured outputs *(c)* Control inputs *(d)* Measured outputs

Fig. 2. Fault free case (a-b) and faulty case (c-d)



(a) μ_1 estimation *(b)* μ_2 estimation *(c)* μ_3 estimation

Fig. 3. Parameters



(a) w_1 indicator *(b)* w_2 indicator

Fig. 4. Residuals

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