Operating mode recognition. Application to a grinding mill process

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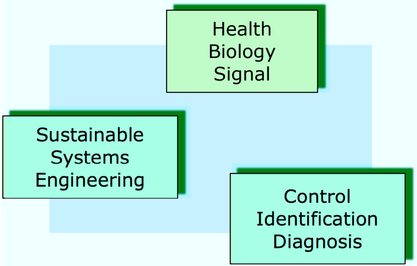
IFACMMM2016 vienna

August 31-September 2, 2016

Founded in 1980, in Nancy, the Research Center for Automatic Control (CRAN) is a joint research unit between the University of Lorraine and the French National Scientific Research Center (CNRS). The unit is also supported by the Lorraine Institute of Oncology (ICL - Alexis Vautrin) and hosts hospital practitioners from the University Hospital Center (CHU).

The CRAN totals 200 persons. The main research activity domains are dynamical control and observation of complex systems, system identification and signal processing, manufacturing plant control, networked control systems, fault detection and fault tolerant control, safety and reliability, health engineering for oncology and neurology. These activities are developed in three research departments.

- Control, Identification and Diagnosis
- Sustainable System Engineering
- Health, Biology, Signal



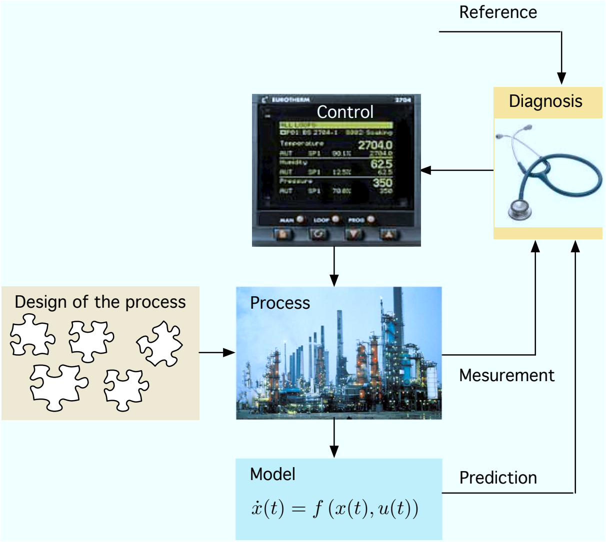
Some types of anomalies

- Abnormal values in data
- Jumps, peaks and shifts in signal
- Anomalies in process components
- Abnormal operations in a process

Methods and tools

- State observers
- PCA, GPCA, KPCA
- Parametric estimation (identification)
- Redundancy degree analysis
- Residual generation for anomalies detection

1. A short presentation of process diagnosis



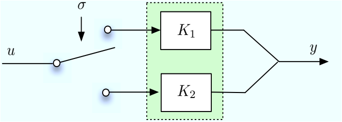
For the elaboration of a global approach for the design and the operation (supervision, maintenance, reconfiguration) of complex automated industrial systems, to guarantee the system safety it is necessary :

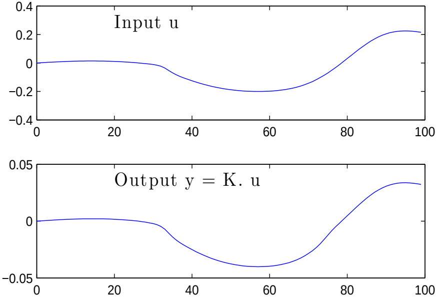
- to detect any fault
- to isolate each fault
- to identify each fault
- to compensate the fault influence

More difficult !

- evaluate the severity of the fault
- predict the evolution of the fault

- A toy example

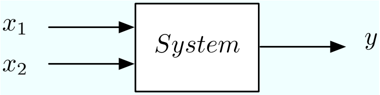




Knowing $u(t), y(t)$, is it possible to detect changes in K ?

Is it possible to detect the mode switching time ?

- Here, a simple solution : analyze the ration $y(t)/u(t)$.
  But this approach can not be generalized



▶ The system behaviour is described at a particular time instant k by one of the two models M_a or M_b

$$\begin{aligned} M_a &: \; y(k) = a_1 x_1(k) + a_2 x_2(k) \\ M_b &: \; y(k) = b_1 x_1(k) + b_2 x_2(k) \end{aligned}$$

▶ The parameters of the two local models are unknown.

▶ At each time instant, from the measurement triple $y(k), x_1(k), x_2(k)$, it is desirable to identify the operating mode of the system.

▶ As the parameters a_i and b_i of the models are unknow, a matching test of the measurement triple to M_a or M_b is not possible.

▶ In fact the measurement triple checks either M_a or M_b and thus verifies the global model defined by the following multiplicative form :

$$\begin{aligned} r(k) &= (y(k) - a_1 x_1(k) - a_2 x_2(k)) \times (y(k) - b_1 x_1(k) - b_2 x_2(k)) \\ &= 0 \end{aligned}$$

$$\begin{aligned} r(k) &= (y(k) - a_1 x_1(k) - a_2 x_2(k)) \times (y(k) - b_1 x_1(k) - b_2 x_2(k)) \\ &= 0 \end{aligned}$$

- So the general idea is to use the global model of the system, which is completely independent of the operating mode changes

$$r(k) = \varphi^T(k)\, p \qquad \begin{cases} \varphi = \begin{pmatrix} y^2 & y\,x_1 & y\,x_2 & x_1^2 & x_1\,x_2 & x_2^2 \end{pmatrix}^T \\ p = \begin{pmatrix} p_0 & p_1 & p_2 & p_3 & p_4 & p_5 \end{pmatrix}^T \end{cases}$$

$$p_0\, y(k)^2 + p_1\, y(k)\, x_1(k) + p_2\, x_1(k)^2 + p_3\, y(k)\, x_2(k) + p_4\, x_1(k)\, x_2(k) + p_5\, x_2(k)^2 = 0 \qquad (1)$$

- Relation between p_i, a_i, b_i ?

- Estimating of parameters easy to achieve for the global model.
We assume now that we have a set of measurements collected on the system during a period where it operates according the two modes M_a or M_b.
As the global model (1) is linear in p_i, a classical least squares method can be used for the parameter identification.

- More generally, for system with more than one output variable, the parameters can be easily obtained using a Principal Component Analysis.

$$r(k) = p_0\, y^2(k) + p_1\, y(k)\, x_1(k) + p_2\, x_1^2(k) + p_3\, y(k)\, x_2(k) + p_4\, x_1(k)\, x_2(k) + p_5\, x_2^2(k)$$
$$r(k) = (y(k) - a_1 x_1(k) - a_2 x_2(k)) \times (y(k) - b_1 x_1(k) - b_2 x_2(k))$$

- The gradient $\sigma(k)$ of $r(k)$ with regard the variables $y(k)$, $x_1(k)$ et $x_2(k)$ is :

$$\sigma(k) = \begin{bmatrix} 2p_0 & p_1 & p_3 \\ p_1 & 2p_2 & p_4 \\ p_3 & p_4 & 2p_5 \end{bmatrix} \begin{bmatrix} y(k) \\ x_1(k) \\ x_2(k) \end{bmatrix} \tag{2}$$

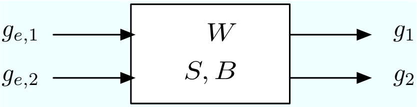
$$\sigma(k) = \begin{bmatrix} 2 & -(a_1+b_1) & -(a_2+b_2) \\ -(a_1+b_1) & 2a_1 b_1 & a_1 b_2 + a_2 b_1 \\ -(a_2+b_2) & a_2 b_1 + a_1 b_2 & 2a_2 b_2 \end{bmatrix} \begin{bmatrix} y(k) \\ x_1(k) \\ x_2(k) \end{bmatrix} \tag{3}$$

- At time k :

If system $\in \; M_a \quad \rightarrow \quad y(k) = a_1 x_1(k) + a_2 x_2(k)$
If system $\in \; M_b \quad \rightarrow \quad y(k) = b_1 x_1(k) + b_2 x_2(k)$.
Substituting these two expressions in (3) leads to :

$$\sigma_a(k) \;\; // \;\; \begin{bmatrix} 1 \\ -a_1 \\ -a_2 \end{bmatrix} \qquad \sigma_b(k) \;\; // \;\; \begin{bmatrix} 1 \\ -b_1 \\ -b_2 \end{bmatrix} \quad \forall k \tag{4}$$

- Equations (3,4) are used to explain the direction of the gradient.
  Equation (2) is used for computing the gradient and finding the active mode.



- Two sizes interval model

$$\begin{cases} \dot{g}_2(t) = \dfrac{1}{\tau}(g_{e,2}(t) - g_2(t)) - g_2(t)\, s_2 + g_1(t)\, s_1\, b_1 \\ \dot{g}_1(t) = \dfrac{1}{\tau}(g_{e,1}(t) - g_1(t)) - g_1(t)\, s_1 \end{cases}$$

j ▶ At steady state, the expression of the output granularity can be deduced :

$$\begin{cases} g_1 & = & \gamma g_{e,1} \\ g_2 & = & \alpha\, g_{e,1} + \beta\, b\, g_{e,2} \end{cases} \qquad \alpha, \beta, \gamma = f(s_1, s_2, b_1) \tag{5}$$

- Besides, it's possible to consider an interrelated output model eliminating the $g_{e,1}$ variable between the two equations (4) :

$$g_2 = \delta\, g_1 + \beta\, g_{e,2}$$

with :

$$\delta = \frac{\alpha}{\gamma}$$

- Local models with two modes of functioning

$$\begin{cases} g_1 - \gamma g_{e,1} & = & 0 & \qquad \gamma = \{\gamma_a,\ \gamma_b\} \\ g_2 - \alpha\, g_{e,1} - \beta\, b\, g_{e,2} & = & 0 & \qquad \alpha = \{\alpha_a,\ \alpha_b\},\ \beta = \{\beta_a,\ \beta_b\} \\ g_2 - \delta\, g_1 - \beta\, g_{e,2} & = & 0 & \qquad \delta = \{\delta_a,\ \delta_b\} \end{cases}$$

- Global model as a product of local models

$$\begin{cases} r_1 & = & (g_1 - \gamma_a\, g_{e,1})(g_1 - \gamma_b\, g_{e,1}) \\ r_2 & = & (g_2 - \alpha_a\, g_{e,1} - \beta_a g_{e,2})(g_2 - \alpha_b\, g_{e,1} - \beta_b g_{e,2}) \\ r_3 & = & (g_2 - \delta_a\, g_1 - \beta_a\, g_{e,2})(g_2 - \delta_b\, g_1 - \beta_b\, g_{e,2}) \end{cases}$$

- Gradient of r_1, r_2, r_3

$$\ldots$$

3.3. Application. Simplified model of a mill process

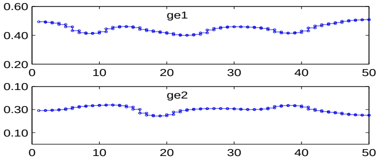
- Global model as a product of local models

$$\begin{cases} r_1 = (g_1 - \gamma_a g_{e,1})(g_1 - \gamma_b g_{e,1}) \\ r_2 = (g_2 - \alpha_a g_{e,1} - \beta_a g_{e,2})(g_2 - \alpha_b g_{e,1} - \beta_b g_{e,2}) \\ r_3 = (g_2 - \delta_a g_1 - \beta_a g_{e,2})(g_2 - \delta_b g_1 - \beta_b g_{e,2}) \end{cases}$$

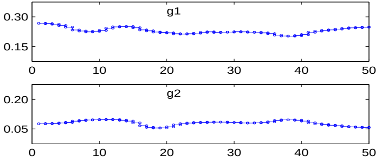
- Occurrences table

	s_1	s_2	b_1
α	$\times$	$\times$	$\times$
β	.	$\times$	.
γ	$\times$	.	.
δ	$\times$	$\times$	$\times$
r_1	$\times$	.	.
r_2	$\times$	$\times$	$\times$
r_3	$\times$	$\times$	$\times$

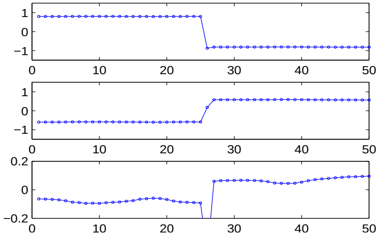
TABLE: Occurrences of variables



Input : size classes 1 and 2



Output : size classes 1 and 2 (with variation of s_1)



Some components of the gradients (of the global models)

- The generalization to a linear system with n input variables x_i is immediate :

$$v(k) = \begin{bmatrix} x_1(k) & x_2(k) & \dots & x_n(k) \end{bmatrix}$$

- The two local modes are then described by :

$$\begin{cases} \text{Mode } a & : & y(k) - a^T v(k) & = & 0 \\ \text{Mode } b & : & y(k) - b^T v(k) & = & 0 \end{cases}$$

- Global model :

$$r(k) = (y(k) - a^T v(k))\,(y(k) - b^T v(k))$$

- Gradient of $r(k)$

...

Whatever time k, the gradient can take only two directions : σ_a and σ_b.

4.2 Generalization : dynamic system

- The generalization to a dynamic linear system is straightforward :

$$v(k) = \begin{bmatrix} x(k) & x(k-1) & \dots & x(k-p) \end{bmatrix}$$

- The two modes are then described by :

$$\left\{ \begin{array}{lcl} \text{Mode } a & : & y(k) - a^T v(k) & = & 0 \\ \text{Mode } b & : & y(k) - b^T v(k) & = & 0 \end{array} \right.$$

- Global model :

$$r(k) = (y(k) - a^T v(k)) \; (y(k) - b^T v(k))$$

- Gradient of $r(k)$

$$\dots$$

- Generalization to a linear system with p operating modes is straightforward :

$$v(k) = \begin{bmatrix} x_1(k) & x_2(k) & \dots & x_n(k) \end{bmatrix}$$

- The modes $a, \dots, p$ are then described by :

$$\begin{cases} \text{Mode } a & : & y(k) - a^T v(k) & = & 0 \\ & \vdots & & & \\ \text{Mode } p & : & y(k) - p^T v(k) & = & 0 \end{cases}$$

- Global model

$$r(k) = (y(k) - a^T v(k)) \dots (y(k) - p^T v(k))$$

- Gradient of $r(k)$

$$\dots$$

Highlights

- Original approach for operating mode recognition
- Knowledge of the models of the modes is not necessary

Upcoming interesting problems

- Robustness with respect to outliers
- Measurement noise influence
- Distance between operating modes
- A more realistic example
- A true application