FAULT DETECTION BY MEANS OF DCS ALGORITHM COMBINED WITH FILTERS BANK

Application to the Tennessee Eastman Challenge Process

Oussama Mustapha, Mohamad Khalil
Lebanese University, Faculty of Engineering, Section I- El Arz Street, El Kobbe, Lebanon
Islamic University of Lebanon, Biomedical Department, Khaldé, Lebanon

Ghaleb Hoblos, Houcine Chafouk
ESIGELEC, IRSEEM, Saint Etienne de Rouvray, France

Dimitri Lefebvre
GREAH – University Le Havre, France

Keywords: Signal processing, Filters Bank, Dynamic Cumulative Sum, Fault detection, Chemical processes.

Abstract: Early fault detection, which reduces the possibility of catastrophic damage, is possible by detecting the change of characteristic features of the signals. The aim of this article is to detect faults in complex industrial systems, like the Tennessee Eastman Challenge Process, through on-line monitoring. The faults that are concerned correspond to a change in frequency components of the signal. The proposed approach combines the filters bank technique, for extracting frequency and energy characteristic features, and the Dynamic Cumulative Sum method (DCS), which is a recursive calculation of the logarithm of the likelihood ratio between two local segments. The method is applied to detect the perturbations that disturb the Tennessee Eastman Challenge Process and may lead the process to shut down.

1 INTRODUCTION

The fault detection and isolation (FDI) methods are of particular importance in industry as long as the early fault detection in industrial systems reduces the personal damages and economical losses. Basically, model-based and data-based methods can be distinguished for diagnosis purposes. Model-based diagnosis requires a sufficiently accurate mathematical model of the process and compares the measured data with the knowledge, provided by the model of the considered system, in order to detect and isolate the faults that disturb the process. Parity space approach, observers design and parameters estimators are well known examples of model-based methods (Blanke and al., 2003; Patton and al., 2000). In contrast, non-model-based diagnosis requires a lot of process measurements and can also be divided into signal processing methods and artificial intelligence approaches. This study continues our research in frequency domain, concerning fault detection by means of filters bank (Mustapha and al., 2007; Mustapha and al., 2007b). The aim of this article is to propose a method for the on-line detection of changes applied after a filters bank decomposition that is needed to explore the frequency and energy components of the signal. The Moving Average (MA) and Auto Regressive Moving Average (ARMA) band pass filters are used to explore the frequency components. The motivation is that the filters bank modeling can transform the frequency changes into energy changes. Then, the Dynamic Cumulative Sum detection method (Khalil and Duchêne, 2000) is applied to the filtered signals (sub-signals) in order to detect any change in the signal. Filters bank is preferred in comparison with wavelet transform (Mustapha and al., 2007) because it could be directly implemented as a real time method.

Mustapha O., Khalil M., Hoblos G., Chafouk H. and Lefebvre D. (2008).
FAULT DETECTION BY MEANS OF DCS ALGORITHM COMBINED WITH FILTERS BANK - Application to the Tennessee Eastman Challenge Process.
In *Proceedings of the Fifth International Conference on Informatics in Control, Automation and Robotics - SPSMC*, pages 102-107
DOI: 10.5220/0001481601020107

2 PROBLEM STATEMENT

This work is originated from the analysis and characterization of random signals. In our case, the recorded signals can be described by a random process $x(t)$ as $x(t) = x_1(t)$ before the point of change t_r and $x(t) = x_2(t)$ after the point of change t_r where t_r is the real time of detection. $x_1(t)$ and $x_2(t)$ can be considered as random processes where the statistical features are unknown but assumed to be identical for each segment 1 or 2. Therefore we assume that the signals $x_1(t)$ and $x_2(t)$ have Gaussian distributions. We will suppose also that the appearance times of the changes are unpredictable. We also suppose that the frequency distribution is an important factor for discriminating between the successive events.

Knowing that the signals from industrial systems are considered as slowly varying non-stationary ones, each change could be identified by its frequency content; our approach assumes piecewise stationary signals and the statistical parameters are the same for the two segments before and after the change. The application of any sequential detection algorithm directly on the original signal will decrease the probability of detection. However, after filters bank decomposition, the frequency change will be transformed into energy change and the detectability of the sequential detection algorithm will be improved. After decomposition of $x(t)$ into N components : $y^{(m)}(t)$, $m = 1,..,N$, the problem of detection can be transformed to an hypothesis test: $H_0 : y^{(m)}(t)$, $t \in \{1,\ldots, t_r\}$ has a probability density function f_0 and $H_1 : y^{(m)}(t)$, $t \in \{ t_r + 1,\ldots, n\}$ has a probability density function f_1.

3 FILTERS BANK TECHNIQUE

In order to explore the frequency and energy components of the original signal, an important pre-processing step is required before detection, feature extraction and classification. At a discrete time t, the signal is first decomposed by using an N-channels band-pass filters bank whose central frequency moves from lowest frequency f_1 up to the highest frequency f_N. Each component $m \in \{1, \ldots, N\}$ is the result of filtering the original signal $x(t)$ by a band-pass filter centered on f_m. The frequency response curves of the filters bank is shown in figure 1. f_N must satisfy the condition $f_N \le f_s/2$, f_s is the sampling frequency of the original signal $x(t)$, N is the number of channels used. The choice of the filters bank depends on the original signal and its frequency band. The number of filters N depends on the details that we have to extract from the signal and to the events that must be distinguished.

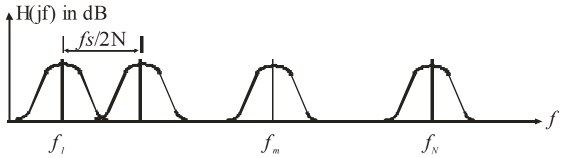

Figure 1: Responses of the filters bank.

The procedure of decomposing $x(t)$ into signals $y^{(m)}(t)$, $m = 1,..,N$, allows us to explore all frequency components of the signal. $y^{(1)}(t)$ gives the low frequency components and $y^{(N)}(t)$ gives the high frequency ones. Therefore, the points of change of each component give information about the frequency and energy contents and will be used to detect any changes in frequency and energy in the original signal.

For each component m, and at any discrete time t, the sample $y^{(m)}(t)$ of an ARMA-type filter is on-line computed according to the original signal $x(t)$ and using the parameters $a_i^{(m)}$ and $b_i^{(m)}$ of the corresponding band-pass filter according to the difference equation (1):

$$y^{(m)}(t) = \sum_{i=0}^{p} b(i)^{(m)} x(t-i) - \sum_{i=1}^{q} a(i)^{(m)} y^{(m)}(t-i) \qquad (1)$$

where $x(t)$ is the input signal of the filter, $y^{(m)}(t)$ is the output signal from the filter m, $a^{(m)}(i)$ and $b^{(m)}(i)$ are the numerator / denominator coefficients of the filter at level m, $a^{(m)}(0) = 1$, $m=1,\ldots,N$, and p and q are the orders of the filter for a given level m, and they are assumed to be identical at any level, for simplicity.

The result of detection depends on the number of the band pass filters used, the central frequencies and the bandwidth of each channel. In practice, filters are uniformly chosen between zero Hertz and the half of the sampling frequency ($fs/2$). For real applications, the choice of the band pass filters are done after comparing the spectral density of two segments (signals $x_1(t)$ and $x_2(t)$). We start with N filters and then reject the filters that do not give energy changes in sub-signals. The technique of comparing the frequency content (deciles or percentiles) is used by many authors to select the best filters (Falou, 2002).

4 SEQUENTIAL ALGORITHMS OF DETECTION

4.1 Cumulative Sum Method

The Cumulative Sum algorithm (CUSUM) is based on a recursive calculation of the logarithm of the likelihood ratios (Basseville and Nikiforov, 1993; Nikiforov, 1986). Let $x_1, x_2, x_3, \ldots, x_t$ be a sequence of observations. Let us assume that the distribution of the process X depends on parameter θ_0 until time t_r and depends on parameter θ_1 after the time t_r. At each time t we compute the sum of logarithms of the likelihood ratios as follows:

$$S_1^{(t,m)} = \sum_{i=1}^{t} s^{(m)}{}_i = \sum_{i=1}^{t} Ln \frac{f_{\theta_1}(x_t / x_{t-1}, \ldots, x_1)}{f_{\theta_0}(x_t / x_{t-1}, \ldots, x_1)} \qquad (2)$$

where, f_θ is the probability density function. The importance of this sum comes from the fact that its sign changes after the point of change. The real point of change t_r can be estimated by t_c:

$$t_c = \max \{t : S_1^{(t,m)} - \min\{i : S_1^{(i,m)}\} = 0\}. \qquad (3)$$

4.2 Dynamic Cumulative Sum Method

The Dynamic Cumulative Sum method (DCS) is based on the local dynamic cumulative sum, around the point of change t_r, and can be used when the parameters of the signal are unknown (Khalil and Duchêne, 2000). It is based on the local cumulative sum of the likelihood ratios between two local segments estimated at the current time t. These two dynamic segments $S_a^{(t)}$ (after t) and $S_b^{(t)}$ (before t) are estimated by using two windows of width W (figure 2) before and after the instant t as follows:

- $S_b^{(t)} : x_i ; \mathrm{i} = \{t - W, \ldots, t-1\}$ follows a probability density function $f_{\theta_b}(x_i)$
- $S_a^{(t)} : x_i ; \mathrm{i} = \{t+1, \ldots, t+W\}$ follows a probability density function $f_{\theta_a}(x_i)$

The parameters $\hat{\theta}_b^{(t)}$ of the segment $S_b^{(t)}$, are estimated using W points before the instant t and the parameters $\hat{\theta}_a^{(t)}$ of the segment $S_a^{(t)}$, are estimated using W points after the instant t. At a time t, and for each level m, the DCS is defined as the sum of the logarithm of likelihood ratios from the beginning of the signal up to the time t:

$$DCS^{(m)}(S_a^{(t)}, S_b^{(t)}) = \sum_{i=1}^{t} Ln \frac{f_{\hat{\theta}_a}^{(i)}(x_i)}{f_{\hat{\theta}_b}^{(i)}(x_i)} = \sum_{i=1}^{t} \tilde{s}_i \qquad (4)$$

(Khalil, 1999) proves that the DCS function reaches its maximum at the point of change t_r. The detection function used to estimate the point of change is:

$$g^{(m)}{}_t = \max_{1 \le i \le t} \left[DCS^{(m)}\left(S_a^{(i)}, S_b^{(i)}\right) \right] - DCS^{(m)}\left(S_a^{(t)}, S_b^{(t)}\right) \qquad (5)$$

The instant at which the procedure is stopped is $t_s = \min \{t : g^{(m)}{}_t \ge h\}$, where h is the detection threshold. The point of change is estimated as follows:

$$t_c = \max \{t > 1 : g^{(m)}{}_t = 0\} \qquad (6)$$

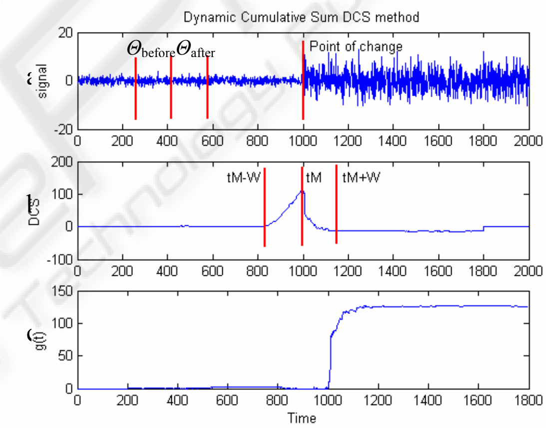

Figure 2: Application of the DCS on a signal of abrupt change. a) Original signal; b) DCS function; c) Detection function *g(t)*.

4.3 DCS Algorithm Combined with MA-type Filters Bank Decomposition

The detection is improved when the DCS method is applied after ARMA or MA modeling, especially when the signal presents no abrupt change, and the direct application of the DCS algorithm leads to ambiguous results that are sometimes difficult to interpret for accurate fault detection. In case of MA modeling, (i.e. $a_i = 0$), equation (2) leads to (7):

$$y^{(m)}(t) = \sum_{i=0}^{p} b(i)^{(m)} x(t-i) \qquad (7)$$

In (Mustapha and al., 2007b), the detectability of the DCS algorithm after MA – type filters bank is proved. The basic idea is to prove that a change in a parameter is equivalent to a change of the sign of the expectation of the logarithm of the likelihood ratio: before the instant of change, $E(\tilde{S}_t) > 0$ and after instant of change $E(\tilde{S}_t) < 0$ where :

$$\tilde{S}_t = Ln(S_t) = \frac{1}{2}[Ln\frac{(\sigma_a^2)^{(t)}}{(\sigma_b^2)^{(t)}} + x_t^2(\frac{1}{(\sigma_a^2)^{(t)}} - \frac{1}{(\sigma_b^2)^{(t)}})] \quad (8)$$

and $(\sigma_a)^{(t)}$ stands for the variance of the segment $S_a^{(t)}$ and $(\sigma_b)^{(t)}$ for the variance of the segment $S_b^{(t)}$. For MA filter and assuming that the successive samples of *x(t)* are independent, (8) leads to (9):

$$E\left[\tilde{S}_t\right] = E\left[Ln(S_t)\right] = E\left[\frac{1}{2}Ln\frac{(\gamma_a^{(t)})^2}{(\gamma_b^{(t)})^2} + \frac{1}{2}\sum_{i=0}^{n} b^2(i)x^2(t-i)\frac{1}{(\gamma_a^{(t)})^2} - \frac{1}{2}\sum_{i=0}^{n} b^2(i)x^2(t-i)\frac{1}{(\gamma_b^{(t)})^2})\right] \quad (9)$$

For $t < t_r - W$, $S_a^{(t)}$ and $S_b^{(t)}$ are identical and have the same characteristics so, $E(\tilde{S}_t) = 0$. For $t_r - W < t < t_r$, $S_a^{(t)}$ and $S_b^{(t)}$ are no longer identical and $E(\tilde{S}_t) > 0$, and for $t_r < t < t_r + W$ we have $E(\tilde{S}_t) < 0$. Finally for $t > t_r + W$, $S_a^{(t)}$ and $S_b^{(t)}$ are identical again and $E(\tilde{S}_t) = 0$.

This demonstrates that $\tilde{S}_t$ increases before t_r, reaches a maximum at t_r then decreases. So, in order to detect the point of change t_r, we search to detect the maximum of $\tilde{S}_t$ by using the detection function g_t.

5 FUSION TECHNIQUE

Because the detection algorithm is applied individually to each frequency component, it is important to apply a fusion technique to the resulting times of change in order to get a single value for a given fault in the system. The fusion technique is achieved as follows:

- -Each point of change at a given level is considered as an interval $[t_c-a, t_c+a]$, where a is an arbitrary number of points taken before and after the point of change.
- -All the time intervals that have a common time area are considered to correspond to the same fault.
- -The resulting point of change t_f is calculated as the center of gravity (or mean) of the superimposed intervals.

6 APPLICATION TO TECP

In this section, the method, based on filters bank decomposition and DCS algorithm, is applied to detect disturbances on the Tennessee Eastman Challenge Process (TECP; Downs and Vogel, 1993). The TECP is a multivariable non-linear, high dimensionality, unstable open-loop chemical reactor, that is a simulation of a real chemical plant provided by the Eastman company. There are 20 disturbances IDV1 through IDV20 that could be simulated (Downs and Vogel, 1993; Singhal, 2000). The sampling period for measurements is 60 seconds.

The TECP offers numerous opportunities for control and fault detection and isolation studies. In this work, we use a robust adaptive multivariable (4 inputs and 4 outputs) RTRL neural networks controller (Leclercq and al., 2005; Zerkaoui and al., 2007) This controller compensates all perturbations IDV1 to IDV 20 excepted IDV1, IDV6 and IDV7.

The figure 3 illustrates the advantage of our method to detect changes for real world FDI applications. Measurements of the reactor temperature (figure 3a) are decomposed into 3 components and according a 3 – channels band pass filters bank (figure 3c, d, e). The sampling frequency of this signal is 0.0167 Hz and the normalized central frequencies of the filters are: f_{c1} = 0.64, f_{c2} = 0.74, f_{c3} = 0.77. From time t_r = 600 hours, the unknown perturbation IDV16 modifies the dynamic behavior of the system. The detection functions applied on the 3 components (figure 3f, g, h) can be compared with the detection function applied directly on the measurement of pressure (figure 3b).

The detection results are considerably improved by using the filters bank as a -preprocessing. In that case, the DCS applied on original signal is not suitable to detect the perturbation whereas the DCS combined with 3- channels band pass filters bank can detect the perturbation. After fusion, the estimated instant of change is t_f = 669 hours that include a large delay to detection of 69 hours.

Table 1: Detection delays for several perturbations in TECP.

Disturbance	Significance	*T°*	*Pr*	*sepL*	*StrL*
IDV 2	B composition, A/C ratio constant (step)	599/677	601/ 665	510/ 535	502/518
IDV 3	D feed temperature (step)	665/680	X	X	X
IDV 4	Reactor cooling water inlet temperature (step)	602/603	X	X	X
IDV 8	A, B, C feed composition (random variation)	650/660	650/660	513/634	343/353
IDV 9	D feed temperature (random variation)	279/287	X	X	X
IDV 11	Reactor cooling water inlet temperature (random variation)	607/608	X	X	X
IDV 16	Unknown	647/670	X	X	X
IDV 17	Unknown	660/850	X	X	X

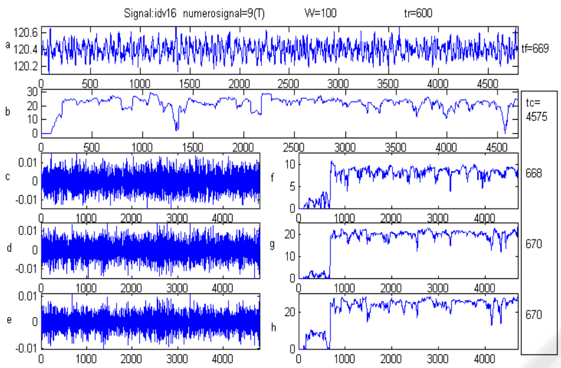

Figure 3: Analysis of the reactor temperature measurements (°C) for TECP with robust adaptive control and for IDV 16 perturbation from t_r = 600. a) Original signal b) DCS applied directly on the original signal c) d) e)Decomposition using band pass filters(m = 1,2,3) f) g) h) Detection functions applied on the filtered signals (c, d, e).

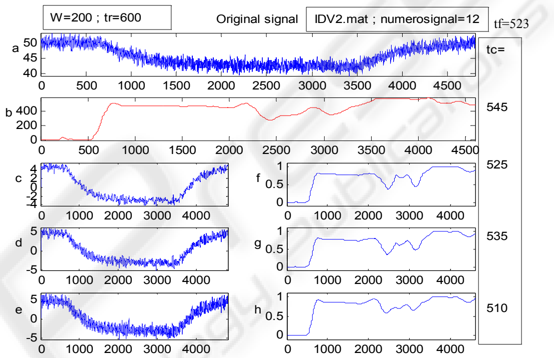

Figure 4: Analysis of the reactor separator level (%) for TECP with robust adaptive control and for IDV 2 perturbation from t_r = 600. a) Original signal b) DCS applied directly on the original signal c) d) e)Decomposition using band pass filters (m = 1,2,3) f) g) h) Detection functions applied on the filtered signals (c, d, e).

The diagnosis of numerous perturbations has been investigated with our method in order to show the efficiency of the approach. All perturbations have been simulated starting from time t_r = 600 hours. The table 1 shows the results obtained with various measured signals and various perturbations. Two studies have been considered:

- For perturbations IDV 2 – 3 – 4 – 8 – 9 – 11 –16 –17, the detection has been investigated in a systematic way from the measurements of temperature in reactor.
- For perturbations IDV 2 and IDV 9, the detection has been compared depending on the measured variable (*T, Pr, StrL, SepL*).

Table 1 shows the minimal and maximal values of t_c obtained over the three components. The detection of changes was satisfactory in most cases depending on the measured signals and the filters that have been used. It is already important to notice that IDV 2, that consists in a step in B composition, cannot be detected with Y_3 and Y_4 (dark grey cells). This perturbation corresponds to a modification of the mean value that can be detected with other methods (figure 4). IDV 8 and IDV 9 also present some difficulties with some measured variable. But an adaptation of threshold h used with detection function and an adaptation of the central decomposition frequencies will lead to acceptable results. One can also notice the large dispersion of the detection times in some cases.

7 CONCLUSIONS

The aim of our work is to detect the point of change of statistical parameters in signals issued from complex industrial processes. This method uses a band-pass filters bank combined with DCS to characterize and classify the parameters of a signal in order to detect any variation of the statistical parameters due to any change in frequency and energy. The proposed algorithm provides good results for the detection of frequency changes in the signal and can be used to detect the perturbation of chemical processes as the TECP under stable closed loop control. The results illustrate the interest of the approach for on – line detection and real world applications. Changes due to faults are easily separated from changes due to input variations by the comparative analysis of input and output signals.

In the future, we will investigate detectability in case of abrupt variations of the mean (figure 4). We will also consider multiple faults investigation and fault isolation based on signatures table of faults. Fault isolation can be studied according to the classification of the changes that are detected and can certainly be improved by increasing the number of considered filters and adapting their central frequencies. We will also study the automatic adaptation of the detection threshold *h* and complete the diagnosis with faults identification.

REFERENCES

Basseville M., Nikiforov I. *Detection of Abrupt Changes: Theory and Application*. Prentice-Hall, Englewood Cliffs, NJ, 1993.

Blanke M., Kinnaert M., Lunze J., Staroswiecki M., *Diagnosis and fault tolerant control*, Springer Verlag, New York, 2003.

Downs, J.J., Vogel, E.F, A plant-wide industrial control problem, *Computers and Chemical Engineering,* 17, pp. 245-255, 1993.

Falou W., "Une approche de la segmentation dans des signaux de longue durée fortement bruités. Application en ergonomie", PhD. Thesis, Université de Technologie de Troyes, France, 2002.

Khalil M., Une approche pour la détection fondée sur une somme cumulée dynamique associée à une décomposition multiéchelle. Application à l'EMG utérin. *Dix-septième Colloque GRETSI sur le traitement du signal et des images*, Vannes, France,1999.

M. Khalil, J. Duchêne. Uterine EMG Analyzing: A dynamic approach for change detection and classification. *IEEE Transactions on Biomedical Engineering, vol. 46, N6, pp. 748-756, juin 2000.*

Leclercq, E., Druaux, F. Lefebvre, D., Zerkaoui, S., Autonomous learning algorithm for fully connected recurrent networks. *Neurocomputing*, vol. 63, pp. 25-44, 2005.

Mustapha O., Khalil M., Hoblos G, Chafouk H., Ziadeh H., Lefebvre D., About the Detectability of DCS Algorithm Combined with Filters Bank, *Qualita 2007*, Tanger, Maroc, 2007.

Nikiforov I. Sequential detection of changes in stochastic systems. *Lecture notes in Control and information Sciences*, NY, USA, pp. 216-228, 1986.

Patton R.J., Frank P.M. and Clarck R., *Issue of Fault diagnosis for dynamic systems*, Springer Verlag, 2000.

Singhal, A., Tennessee Eastman Plant Simulation with Base Control System of McAvoy and Ye., *Research report, Department of Chemical Engineering,* University of California, Santa Barbara, USA, 2000.

Zerkaoui S., Druaux F., Leclercq E., Lefebvre D., Multivariable adaptive control for non-linear systems : application to the Tennessee Eastman Challenge Process, *ECC 2007*, Kos, Greece, 2007.