HYBRID ALGORITHMS FOR THE PARAMETER ESTIMATE USING FAULT DETECTION, AND REACHING CAPACITIES

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Abstract: The nonstationary systems parametric estimate requires the continuation of its parameters which vary abruptly at unknown random moments. These are the abrupt parametric variations which were considered in this work to be managed like ”faults”. The considered signals here are nonstationary and are characterized by time variable parameters. The estimate of these parameters requires the choice of an algorithm having the capacity to continue their evolution. The various hybrid adaptive estimate methods showed that these capacities can be reached by a compensation of a gain and its update in online. In this paper, a method of estimate is proposed, based on the fault detection. The general algorithm implemented gives place to several methods which will be detailed. Experimental tests of some methods on a second order autoregressive synthesis signal are carried out and then commented.

1 INTRODUCTION

For several years, the fault detection, or abrupt changes of one or several parameters, has given place to many work (Frank, 1996) in very varied applicability like the dynamic systems control (J. Ragot and Ribbens, 1993), the defects or breakdowns detection of the controlled systems (Wagner and Shoureshi, 1992; Magaldi, 1997), the biomedical diagnosis (Corge and Puech, 1986), the speech proc-essing for the recognition and the image processing (Basseville, 1982) and the signal adaptive processing (A. Kobi and Ragot, 1994). In this work, one is interested to the nonstationary systems parametric estimate characterized by time variable parameters which presents abrupt variations regarded here as faults, and whose estimate requires an algorithm able to follow their evolution (Macchi and Turki, 1992).

It is presented a complete procedure of a method combining the adaptive methods and the fault detection for nonstationary signals. A general algorithm of parametric estimate is established, giving place to several under-algorithms. Experimental tests are carried out on a second order autoregressive synthesis signal, noted AR2.

2 HYBRID ADAPTIVE ESTIMATE METHODS

These methods show that it is possible to approach the real parameters by a compensation Ω of the gain P, in its update which we describe in his hybrid form (1):

$$\begin{aligned} \rho P\left(t\right) &= -\bar{P}\left(t\right) + \Omega\left(t\right) \\ \bar{P}\left(t\right) &\triangleq \frac{\alpha(t)P(t)\varphi(t)\varphi^T(t)P(t)}{\Gamma(t)+T_e\varphi^T(t)P(t)\varphi(t)} \end{aligned} \tag{1}$$

where $\alpha(t)$ is a positive weight function $\forall t$ and $\Gamma(t)$ a standardization term > 0. $\Omega(t)$ is an update function, of the gain $P(t)$, representing the covariance estimate of the parametric variations. T_e is the sampling period.

The choice of $\Omega(t)$ and of the compensation procedure define the hybrid adaptive estimate method (HAEM) considered. One can group the various HAEM in 2 kinds:

- **The HAEM with ”*continue*” compensation of gain:**

  $\Omega\left(t\right) \triangleq$ function of time t. The compensation of gain is done with each iteration; it is the case of methods with forgetting factor.

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- **The HAEM with compensation of gain after detection of fault** (2):

$$\begin{array}{l}\Omega\left(t\right)\triangleq\Omega_{0}\left(t\right)\delta\left(t-t_{r}\right)\\ \Longrightarrow\left\{\begin{array}{ll}\Omega\left(t\right)=0 & if\quad t\neq t_{r}\\ \Omega\left(t\right)=\Omega_{0}\left(t\right) & if\quad t=t_{r}\end{array}\right.\end{array}\tag{2}$$

  where $\Omega_0(t)$ is the amplitude of the update fonction $\Omega(t)$, t_r the fault moment, and $\delta(t-t_r)$ the Dirac impulse at moment $t-t_r$. $\Omega_0(t_r)$ is the compensation term who expresses himself either according to the Fisher Information matrix (FIM), or according to the covariance matrix (CovMat). Its expression is carried out in the q^{-1} recursive case and the δ recursive case.

3 HYBRID ADAPTIVE PARAMETRIC ESTIMATE BY FAULT DETECTION

The principle is: as soon as a fault is detected, it is necessary to act immediately on the estimate algorithm to correct the adaptation gain and to enable him to compensate the fault while choosing well $\Omega_0(t)$. This gives place to several methods whose essential idea is to couple an estimate algorithm with a fault detection algorithm.

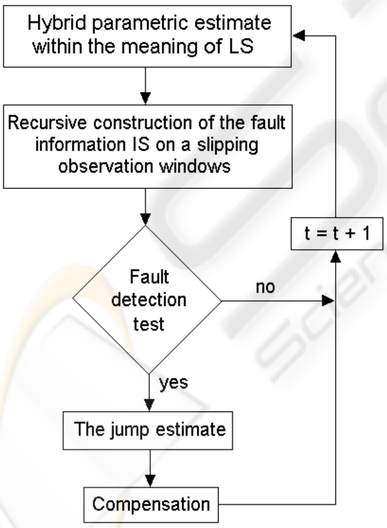

Figure 1: Principle of the hybrid adaptive parametric estimate controlled by fault detection.

The procedure suggested uses as criterion the Recursive Least Squares (RLS) (Goodwin and Middleton, 1990). The algorithm is built in manner that with each step, a detector tests fault information by carrying out an hypothesis test based either on a confidence interval (Bendat and Piersol, 1999), or on the probability ratio (Tanaka and Muller, 1990). The use of a confidence interval makes it possible to decide the existence of a fault whatever the adopted model (AR[1] or ARMA[2]). The detector has the capacity to decide to rectify the consequently algorithm according to the diagram of the figure (1).

Table 1: The alternatives of the HAEM by fault detection.

Detection test	operator	Compensation
χ^2	derivative δ	FIM or CovMat
χ^2	delay q^{-1}	FIM or CovMat
Fisher	derivative δ	FIM or CovMat
Fisher	delay q^{-1}	FIM or CovMat
Student	derivative δ	FIM or CovMat
Student	delay q^{-1}	FIM or CovMat
RDPR	derivative δ	FIM or CovMat
RDPR	delay q^{-1}	FIM or CovMat

The algorithm proposed is structured as follows: on a basis kind MCR are grafted three successive phases which are the construction of an Information Signal IS, the test of fault detection and the compensation of the detected fault. According to the choice of the nature of each one of these 3 phases, it was elaborate several alternatives of the method thus giving place to eight different tests for an operator given (q or δ) which are grouped in table (1).

The detection tests apply to the signal IS and are based on the Probability Ratio PR (test built on the recursive deviation of the PR and called RDPR) and/or the interval confidence built using the distributions χ^2 or Fisher or Student. The compensation procedure is carried out in an indirect way: the adaptation gain is corrected in real time by the intermediary of a function either of the Fisher Information Matrix (FIM) or of the Covariance Matrix of the parametric drift (CovMat) (Tab. 1).

3.1 The global hybrid algorithm

The global algorithm of the whole of the HAEM by fault detection methods proposed in figure (1) is based on the equations (3) and (4), and corresponding to equations (5-12) of table (2) for the case $\alpha\left(t\right)=\Gamma\left(t\right)=1$.

$$\rho\hat{\theta}\left(t\right)=\frac{\alpha\left(t\right)P\left(t\right)\varphi\left(t\right)\left[y\left(t\right)-\varphi^{T}\left(t\right)\hat{\theta}\left(t\right)\right]}{\Gamma\left(t\right)+T_{e}\varphi^{T}\left(t\right)P\left(t\right)\varphi\left(t\right)}\tag{3}$$

[1]Auto-Regressif

[2]Auto-regressif with Adjusted Mean

$$\rho P(t) = -\frac{\alpha(t)\,P(t)\,\varphi(t)\,\varphi^T(t)\,P(t)}{\Gamma(t) + T_e\varphi^T(t)\,P(t)\,\varphi(t)} + \Omega(t) \quad (4)$$

where $\alpha(t) \in [0,1]$ is a positive weight function ($\forall t$), $\Gamma(t)$ is the standardization term (> 0) and $\Omega(t)$ the update function covariance matrix or adaptation gain $P(t)$ such as $\Omega(t) = \Omega^T(t) \geq 0$.

Table 2: Hybrid algorithm

the parameter vector:
$\theta(t) = \begin{bmatrix} a_1(t), \cdots, a_n(t), \\ b_1(t), \cdots, b_n(t) \end{bmatrix}^T$ (5)
the measure vector:
$\varphi(t) = [-\rho^{n-1}y(t), \cdots, -\rho y(t), \rho^m u(t), \cdots, u(t)]^T$ (6)
$\rho\hat{\theta}(t) = \frac{P(t)\varphi(t)\varepsilon(t)}{1+T_e\varphi^T(t)P(t)\varphi(t)}$ (7)
$\rho P(t) = -\bar{P}(t) + \Omega(t)$ (8)
$\bar{P}(t) \triangleq \frac{P(t)\varphi(t)\varphi^T(t)P(t)}{1+T_e\varphi^T(t)P(t)\varphi(t)}$ (9)
$\Omega(t) = \Omega_0(t)\,\delta(t - t_r)$ (10)
with the estimated parameter vector:
$\hat{\theta}(t) = \begin{bmatrix} \hat{a}_1(t), \cdots, \hat{a}_n(t), \\ \hat{b}_1(t), \cdots, \hat{b}_n(t) \end{bmatrix}^T$ (11)
$P(t)$ is the adaptation gain, T_e is the sampling period and t_r is the fault moment. $\Omega_0(t)$ is the update function of the gain.
The prediciton error is such as: $\varepsilon(t) = y(t) - \varphi^T(t)\,\hat{\theta}(t)$ (12)

4 EXPERIMENTAL TESTS AND RESULTS

Some various algorithms of table (1) were applied to a 2nd order autoregressive synthesis test signal noted AR2, and their performances were tested on this signal.

4.1 Construction of the test signal

The AR2 test signal built is given by the figure (2a), and it is fed by a generating white noise $\eta(t)$ (figure 2c). The variations of the two parameters a_1 and a_2 are represented on the figure (2b). The figure (2d) shows the AR2 spectral density.

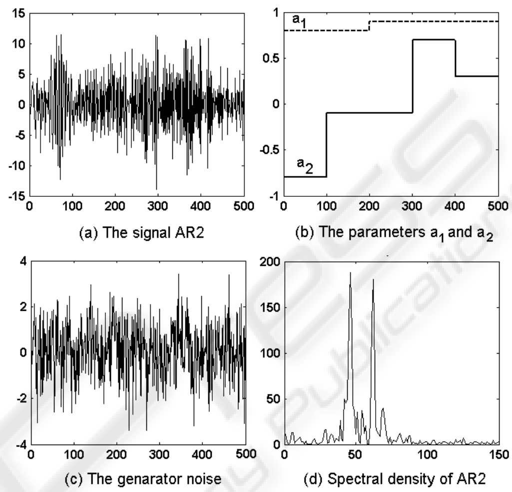

Figure 2: Construction of the AR2 Signal test.

4.2 Application of the algorithms

The estimate algorithms by fault detection ($Fisher$ and $Student$), the simple RLS algorithm and the RLS algorithm with constant forgetting factor, for the delay operator q^{-1} (Tab. 1), were applied to AR2 test signal in order to obtain the estimate of the parameters $a_1(k)$ and $a_2(k)$.

4.2.1 simple RLS algorithm

The figures (3a) and (3b) shows the estimate of the parameters $a_1(k)$ and $a_2(k)$.

The natural decrease of the adaptation gain of the parameter a_2 (figure 3f) can be noticed, where the estimate error is very important.

The simple RLS algorithm can not follow the parameter variations.

4.2.2 RLS algorithm with constant forgetting factor

The figures (3c) and (3d) gives the results of the estimate.

The estimate approaches the true value, the gain (figure 3e) is maintained sufficiently to follow the parametric variations.

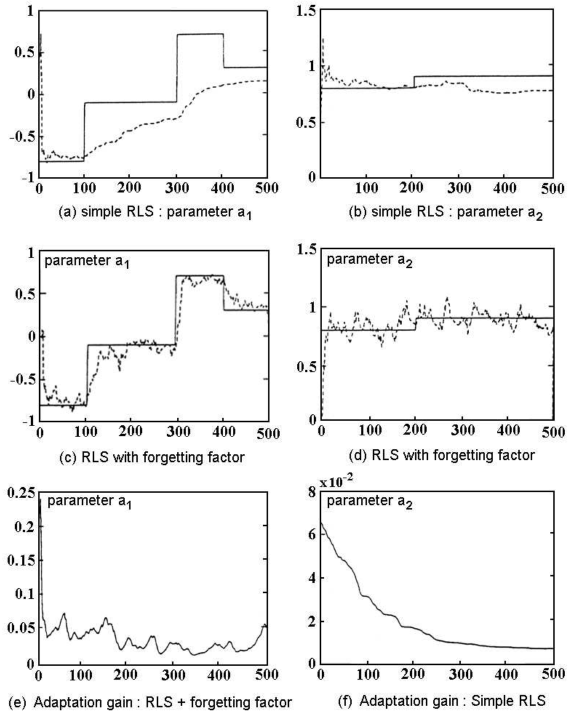

Figure 3: Parametric estimate by the RLS method.

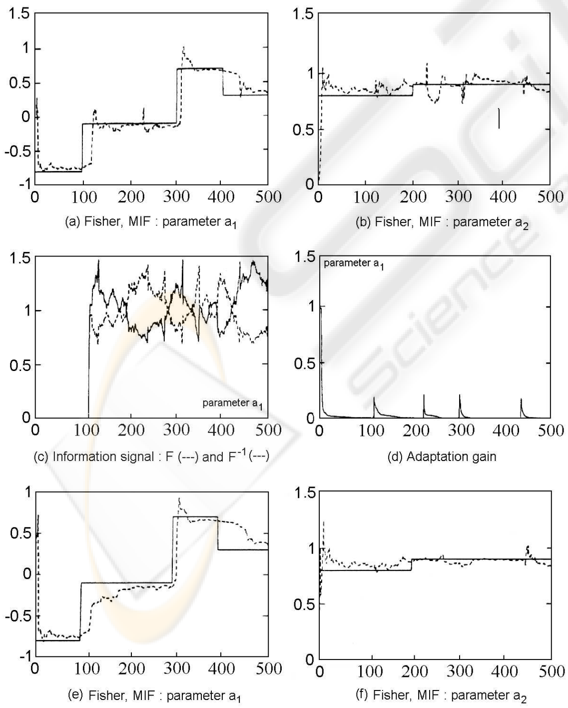

Figure 4: Parametric estimate with fault detection: Fisher test with FIM.

4.2.3 Fisher test - *Fisher detection* algorithm and *FIM* compensation

With as information signal the prediction gain and its reverse, the figures (4a) and (4b) gives the estimates.

The figure (4c) shows the confidence interval for the Fisher test and its reverse, and the figure (4d) shows the adaptation gain. The detected fault are: $t_{r_i} = 120, 228, 306$ et 436.

The influence of the window size is visible by looking at the figures (4a) and (4e) jointly for the parameter a_1 and the figures (4b) and (4f)) jointly for the parameter a_2, for $nb_1 = 60$ and $nb_2 = 120$.

4.2.4 Fisher test - *Fisher detection* algorithm and *CovMat* compensation

With the used data information below :

- information signal: the prediction gain and its reverse,
- window widths: $nb_1 = 80$ and $nb_2 = 100$,
- confidence interval: 90%,
- $s_0 = 0.01$,
- temporization: $t_p = 40$,

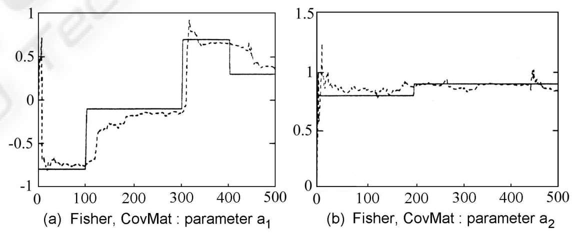

Figure 5: Parametric estimate with fault detection: Fisher test with CovMat.

and for a compensation by the covariance matrix of $\frac{\Delta\hat{\theta}}{\hat{\theta}}$, the obtained results are shown on the figures (5a) and (5b); one obtains a very good estimate in spite of false alarm and the light delay.

The estimated fault moments are $t_{r_i} = 120, 264, 308$ et 440.

4.2.5 Student test with *FIM/CovMat* compensation

The figures (6a) and (6b) shows the estimated obtained by the FIM compensation and the figures (6c) and (6d) by the CovMat compensation.

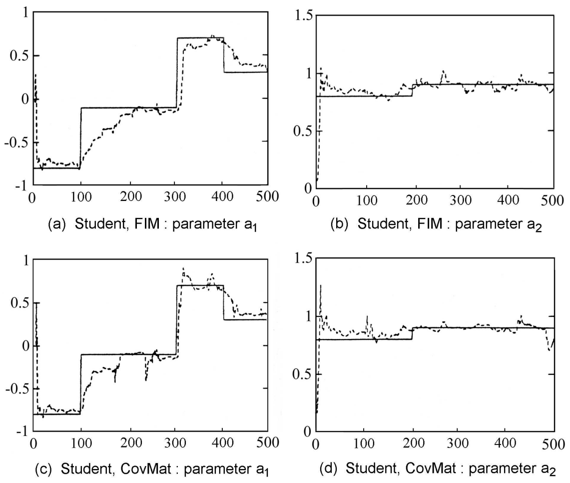

Figure 6: Parametric estimate with fault detection: Student test.

5 CONCLUSION

It was shown that the fault detection algorithms provide estimated which follow very well the fault and convergent in spite of the fact that some algorithms give false alarm or nondetections. The elaborate algorithms were applied to nonstationary test signals with different choices of signal information for the detection test. This variety of application will give results which illustrate and make it possible to highlight several properties of the nonstationary signal processing by fault detection for the q^{-1} operator. It was shown also that the statistical tests χ^2, Fisher and Student can be applied to detect nonstationnarities of the test signals. Associated to an estimate and compensation algorithm, these tests make it possible to follow nonstationnarities, even brutal, and to increase the performances of the algorithm by reducing the skew of the estimate and by increasing their capacity of continuation. The number of the selected information signals (FIM, CovMat) will increase the number of alternatives of the hybrid adaptive estimate method by fault detection suggested, that is to say higher than 8 alternatives. An establishment of all these alternatives would give an overall assessment, therefore to know the good method carrying out one better estimate. A comparative study between the application of the q^{-1} algorithms and δ algortithms would be interesting to deduce the methods ensuring a good estimate and a better capacity of continuation.

REFERENCES

A. Kobi, S. N. and Ragot, J. (1994). Fault detection isolation and control reconfiguration. *2nd International Symposium on Mathematical and Intelligent Models in System Simulation. IMACS*, 37:111–117.

Basseville, M. (1982). Sequential detection of abrupt changes in spectral characteristics of digital signals. *IEEE Symposium on Information Theory - ISIT'82*, pages 21–25.

Bendat, J. S. and Piersol, A. G. (1999). Random data analysis and measurement procedures. *John Wiley Sons Inc., New york*.

Corge and Puech (1986). cardiac rate analysis by fault detection methods (in french). *Proceedings INRIA, 7th ICAOS Antibes 1986, France*.

Frank, P. M. (1996). Analytical and qualitative model-based fault diagnosis - a survey and some new results. *European Journal of Control*, 2(1):6–23.

Goodwin, G. C. and Middleton, R. H. (1990). Digital control and estimation. a unified approach. *Prentice Hall, New York*.

J. Ragot, D. M. and Ribbens, W. B. (1993). Two approaches for the isolation of plant railures in dynamic systems. *International Conference on fuit diagnosis, Tooldiag Toulouse*, 3:24–28.

Macchi, O. and Turki, M. (1992). The nonstationary degree: can an adaptive filter be worse than no processing. *journal of the International Federation of Accountants IFAC - ACASP 92*, 1:48–63.

Magaldi, R. (1997). Dealing with the failure in the real world: a human factors engineering approach. *Proceedings of the Second International Conference on Case-Based Reasoning Research and Development*, 1266:114–121.

Tanaka, S. and Muller, P. C. (1990). Fault detection in linear discrete dynamic systems by a pattern recognition of a generalized l.r. *Journal of Dynamic Systems, Measurements and Control. Transactions on ASME*, 112.

Wagner, J. and Shoureshi, R. (1992). Failure detection diagnostics for thermofluid systems. *Journal of Dynamic Systems, Measurement and Control. Transactions on ASME*, 114:699–706.