FAULT DETECTION TECHNIQUES ANALYSIS AND DEVELOPPMENT OF ITS PROCEDURAL PHASES

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ABSTRACT

To carry out a diagnosis, or detect an abrupt change or fault in dynamic behavior of a studied or supervised system (signal, system or model), on-line or off-line (according to the treated case), it is imperative to develop an installation strategy of a diagnosis tool.

In this paper, various techniques of fault detection are presented. The role of hypothesis test as tool for fault presence detection or not and the role of the confidence interval in parameter estimation are shown. Then, the principal various phases composing fault detection are proposed and developed.

1. INTRODUCTION

Since the Seventies, the fault or abrupt detection change gave place to many work [1, 2, 3] in very varied application domains like the dynamic systems control [4], the controlled systems defects or breakdowns detection [5, 6, 7, 8, 9, 10], the biomedical diagnosis, speech processing for the recognition [11], image processing [12] and signal adaptive processing [13].

In what follows, the fault detection techniques are presented, then a fault detection procedure is developed and finally a detail is established on several points concerning the fault diagnosis.

2. FAULT DETECTION ANALYSIS

To carry out effectively a detection, it is first of all necessary to define an event carrying the fault information, which will be an indicator of fault. This event constitutes the *Information Signal* IS. And to take effectively this fault into account, the knowledge of its arrival moment or *fault moment* is necessary to proceed either to a compensation by adaptation (case of new behavior: not stationarity), or a correction (case of fault). The decision of fault existence or not requires a decision test established according to a rule to build, which amounts to doing an hypothesis test, which in a simple case can be reduced to:

$$H_0 \; : \; there\ is\ no\ fault$$
$$H_1 \; : \; there\ is\ fault$$

We present, in what follows, the hypothesis test and the *confidence interval*, then we develop the five principal phases constituting the fault detection, namely:

1. *to establish the hypothesis test*
2. *to generate the signal information IS,*
3. *to detect the fault moment,*
4. *to estimate the fault amplitude,*
5. *to compensate the fault.*

2.1 hypothesis tests

To extract the informations and to carry out the five preceding stages, we have a series of observations which can be reliable or not. These observations y^N are those of a random signal realization. The faults problems are based primarily on assumptions tests. So $H_0, ..., H_n$, n equiprobable or not hypothesis, intervening in the system operation. One has a series of observations y_i and observations probability laws conditioned by the hypothesis H_i.

The existing various hypothesis tests are:

- Bayes test
- Neyman-Pearson test
- Multiple hypothesis test
- Composite hypothesis test

2.2 confidence Interval

The existence of a variation $\tilde{} = \hat{} - {}_0$ (${}_0$ generally unknown) called parametric estimation error, justifies a technique of parameter estimating which utilizes the estimating by *interval* in opposition to that of a *specific* value which supposes that the parameter was estimated with a known uncertainty degree [14]. The establishment of this interval is conditioned by the knowledge of the probability density of the estimator. One thus consider a significant level   that allowing to define two distinct areas laying down the decision rule of the hypothesis test; one notes:

$$E_r \; : \; the\ hypothesis\ rejection\ area,$$
$$E_a \; : \; the\ hypothesis\ acceptance\ area.$$

These areas of rejection E_r or acceptance E_a translate the statistical procedure defining the hypothesis test.

3. FAULT DETECTION PROCEDURE

3.1 Information signal choice (IS)

The information signal construction means the definition and the determination of fault information translating accurately and instantaneously the parameter evolution variation. The information signal must represent the fault *signature*. The problem arising is *how to extract* the signature from a fault starting from the system data or informations.

In general, a system is described by the model (figure 1).

$$y = f(u(t),\ \ (t), x(t),\ \ (t)) \quad (1)$$

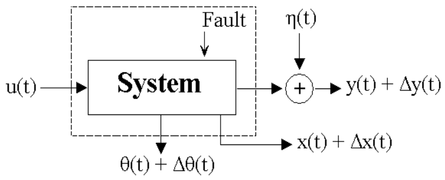

Figure 1: System in fault

where $u(t)$ is the measurable input, $y(t)$ the measurable output, $\ (t)$ the noise, $\ (t)$ the variable parameters and $x(t)$ the state variables.

According to the considered application , the fault can correspond may be with a *normal* system operation but this system is with time varying parameters. It is the case of *non-stationarinesses* whose assumption of responsibility represents all the problems of the parametric estimation for these systems [2, 15], maybe with an *abnormal* system operation; it is about a defect which should absolutely be detected to ensure the safety and the reliability of the system [1]. In both cases, the fault appears in the change of the parameters $\ $, or of the state variables x, which leads to the change of the output y.

There are several approaches according to whether the system modeling is or not possible and according to the nature and the shape of the information signal. One quotes:

- Information signal function of the output [3, 2],
- Information signal function of parametric error,
- Information signal function of the average of the estimated parameters [16],
- Information signal function of the innovation [4, 3, 17],
- Information signal function of the information matrix of Fisher [14].

3.2 Decision test establishment

That means to detect the occurrence of system fault or defect under observation and/or estimation. It should be decided from the information signal, carrying the fault information, so yes or not a fault exists. This binary decision-making must be made as soon as the event "fault" takes place (for the treated on-line systems) and must correspond to the most probable condition. The choice of the decision test depends at the same time on the treated application, the selected information signal and the law on which it is based. What leads to two compromises: between, on the one hand the complexity of the test and its effectiveness, and on the other hand between false alarms and the delay with detection.

We can classify the various procedures of fault detection in the form of three principal groups depending on the choice of the decision test.

- Tests based on the density of conditional probability: We distinguish primarily those which refer to the probability ratio and its derivatives giving place to 3 tests: the maximum of probability, the probability ratio generalized [8] and the Page Hinkley test [2, 17], and those utilizing the distance between two models [11] like example the divergence of Kullback.
- Tests based on the parametric error: These tests relate to information signals function of the parametric error, and are dependent on the choice of a threshold. One quotes like example the tests based on the parametric error covariance and the tests based on the correction of the parameter vector [17].
- Tests based on confidence interval of information signal: These tests refer directly to the information signal distribution, and consequently are function of the confidence interval built on the probability density. One quotes: tests based on the distribution $\ ^2$ [9], the Fisher distribution [14] and the student distribution [14], and tests based on the probability ratio recursive deviation [17].

3.3 Fault compensation

That the estimate of the fault provides or not its amplitude, it is possible to compensate this fault. This very significant phase in an on-line estimation makes possible to correct the defect or fault and in consequence to increase the adaptive estimation algorithm performances. Thus the adaptation can be made even if nonbrutal stationnarities exist, provided that the changes are weak on average. So the algorithm acquires the capacity to prosecute these nonstationnarities.

- The fault can be compensated either on the vector parameter $\hat{\ }(t)$, or state vector $X(t)$, or the output $y(t)$ [17],
- One second procedure of compensation is the indirect compensation by an adaptation gain update $P(t)$ [16].

4. HYBRID ADAPTIVE ESTIMATE METHODS

The detection procedure, as decomposed before, enables us to have:

1. A broad choice of *ISs* which contains the fault,
2. a rather significant number of decision tests which allow the detection of fault in the system parameters, and
3. two general compensation methods of the fault, ones direct and other indirect.

To carry out a complete fault detection and estimate algorithm, it is enough to combine one of the information signals IS with one of the decision tests and one of the compensation methods. Thus, a good number of estimate methods, therefore algorithms, can be obtained. The hybrid adaptive estimate methods study led to conclude that they have the capacity of continuation the parametric variations. There are then several possible approaches such as the Kalman filter, the Recursive Least Squares with forget factor, the fault detection associated either with least squares [16], or with the out of lattice filters [16], or with the observers [4], and the $H\ $ theory [3]. The interest and the facility of the use of the regression techniques lead, very often, to the use of parametric models, linear in the parameters, such linear regression (2).

$$y(t) = \ ^T(t)\ \ (t) + \ \ (t) \quad (2)$$

with $\ (t)$ the unknown parameter vector, $y(t)$ and $\ (t)$ are respectively the system output and and the regression linear vector which are known functions. $\ (t)$ is supposed a white noise with null average and variance $\ ^2$. If the noise is colored of known spectrum, the problem can be brought back to the case of a white noise by a suitable pre-filtering, so that the generated estimate will be optimal. This formulation gathers the linear models AR, ARMA, ARMAX or ARIMAX in the presence of signals drift case, and also the nonlinear models being able to be formulated in a linear way on the parameters (t).

The algorithm of hybrid parametric estimate methods is defined by (3):

$$\begin{aligned} \hat{\ }(t) &= \frac{(t)P(t)\ \ (t)\left[y(t)- \ ^T(t)\ \hat{\ }(t)\right]}{(t)+T_e\ \ ^T(t)P(t)\ \ (t)} \\ P(t) &= -\frac{(t)P(t)\ \ (t)\ \ ^T(t)P(t)}{(t)+T_e\ \ ^T(t)P(t)\ \ (t)} + \ \ (t) \end{aligned} \quad (3)$$

with:

$(t) \in [0,1]$: a positive weight function $\forall t$,

(t) : standardization term > 0; $\ (t) = w(t,\ )^{-1}$,

(t) : update function of covariance matrix and adaptation gain $P(t)$ such as $\ (t) = \ ^T(t) \geq 0$.

The application of this generalized algorithm requires a compromise to be carried out between the capacity of parameters variations continuation and the desired attenuation of noise. A suitable choice of the functions (t) and (t) give place to several possible algorithms, described below.

The function (t) who modifies the covariance matrix P, has as a role to prevent the natural decrease of the gain towards zero: $(t) > 0$ allows to maintain the continuation of parametric variations. The choice of (t) must be justified by a sufficiently large lower limit so that the algorithm manages to follow the variations with a weak delay. This limit can be reached either by maintaining the trace of P constant, either by re-initializing P, either still by choosing (t) such as an update of P towards an adequate value is made when the excitation is weak. In the recursive case, one obtains starting from the generalized algorithm (3), the equations (4) where $\frac{}{T_e}$ is replaced by the constant .

$$\hat{\ }(k) = \hat{\ }(k-1) + \frac{P(k-1)\ \ (k-1)\ \ (k)}{+\ \ ^T(k-1)P(k-1)\ \ (k-1)}$$

$$(k) = y(k) - \ ^T(k-1)\ \hat{\ }(k-1)$$

$$P(k) = P(k-1) - \frac{P(k-1)\ \ (k-1)\ \ ^T(k-1)P(k-1)}{+T_e\ \ ^T(k-1)P(k-1)\ \ (k-1)} + T_e\ \ (k-1) \quad (4)$$

The recursive least squares method is obtained for $\ = 0$ et $\ = \ = 1$.

4.1 The derived different Algorithms

The various algorithms for different expressions of functions (t) and (t) corresponding to derived algorithms from the Least squares hybrid algorithm are:

1. RLS: Recursive Least Squares:

$$(t) = 1; \quad (t) = 0; \quad (t) = 1 \quad (5)$$

2. Gradient:

$$(t) = \frac{(t)P(t)\ \ (t)\ \ ^T(t)P(t)}{(t)+T_e\ \ ^T(t)P(t)\ \ (t)}; \quad (t) = constant \quad (6)$$

3. RLS + forget:

$$\begin{aligned} (t) &= \left[\frac{1}{1-T_e}\right]\left[\ \ P(t) - \frac{T_eP(t)\ \ (t)\ \ ^T(t)P(t)}{(t)+T_e\ \ ^T(t)P(t)\ \ (t)}\right] \\ (t) &= 1; \quad \leq 1 \end{aligned} \quad (7)$$

4. Kalman Filter:

$$(t) = 1; \quad (t) > 0 \quad (8)$$

5. Covariance update:

$$(t) = [P_0 - P(t+T_e)] \sum_{j=1} i\ \ (t-t_j); \quad (t) = 1 \quad (9)$$

6. Constant trace:

$$\begin{aligned} (t) &= \frac{}{C_i}\frac{(\ ^T(t)P^2(t)\ \ (t))P(t)}{(t)+T_e\ \ ^T(t)P(t)\ \ (t)} \\ (t) &= 1;\ C_i = trace(P_0) \end{aligned} \quad (10)$$

7. exponential forget and update:

$$\begin{aligned} (t) &= \ \ (t);\ 0 < \ \ (t) \leq 1 \\ (t) &= 1 + \ \ (t)\ \ ^T(t)\ \ (t); \\ (t) &= \ \ (t)P(t) - \ \ (t)\ \ (t)P^2(t) \end{aligned} \quad (11)$$

5. APPLICATION EXAMPLE

In this example, a simulation is achieved on second order Auto-regressif test signal, the two parameters a_1 and a_2 are the coefficient of the AR model.

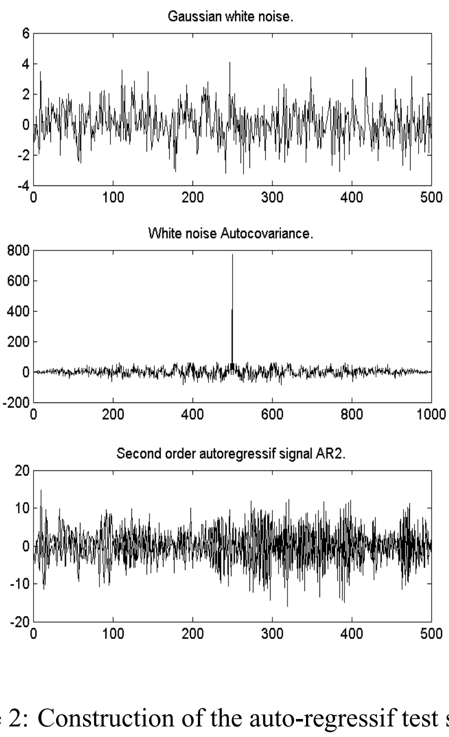

Figure 2: Construction of the auto-regressif test signal.

The decision test used here is the Chi-2 distribution and the fault compensation is the covariance matrix. The figure (2) shows the second order auto-regressif signal, the input signal (gaussian white noise) of the auto-regressif model and the autocovariance of noise. The results of the estimation method using Chi-2 are shown on the figure (3), where faults are simulated on the parameter $a_1(k)$ at the instants $k = 100$, 300 and 400, and on the parameter $a_2(k)$ at the instant $k = 200$. The Chi-2 test detected the faults well even if their compensation took place a little later like visible at the instants $k = 300$ for a_1 and $k = 200$ for a_2.

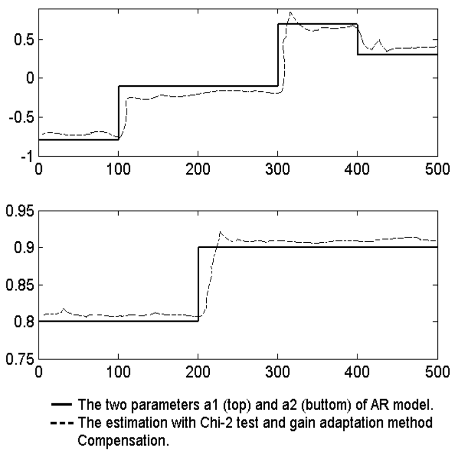

Figure 3: Parametric estimate based on fault detection: Chi-2 distribution test with covariance matrix compensation.

6. CONCLUSION

We have decomposing the fault detection procedure into 5 phases (the information signal IS, the decision test, the fault moment t_r, the fault amplitude and compensation). From this decomposition, we studied the fault detection techniques by quoting several examples existing in the literature.

This development enabled us to stress several points:

1. the fault detection application domain is very varied,
2. Its goal is to generate a system diagnosis under monitoring or control,
3. the available tools for the realization strategy can be done by various approaches in the frequential and/or analytical domain,
4. the used statistical approach is justified by the dubious environment of the fault event,
5. the importance of the hypothesis test role, the confidence interval and the probability density could be highlighted,
6. the Information Signal construction, carrying the fault information, which is preliminary phase to any detection procedure, are primarily based on the estimation errors,
7. the decision tests can form tree principal groups:
    - the tests concerning the density of conditional probability,
    - to base on the parametric error,
    - and those built in the confidence interval of information signal.
8. the fault moment can be estimated,
9. the fault compensation allows to rectify the fault and/or to adapt the system to the new model.

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