FAULT DETECTION AND ISOLATION USING SPECTRAL ANALYSIS

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Abstract: In this work, spectral signal analyses are employed in fault detection and isolation scheme. The procedure was applied to detect the presence of fault in proces and suppose the processing in frequency domain of the data acquisition, which represent the known commands and the actual measure outcome. The approach has been applied to electrical motor and the results show that the fault detection scheme designed can detect incipient faults. Also, the effects of faults on the diagnostic residuals are maximised. The technique was tested by simulation and the results are good.

Key words: Fault detection and isolation, analytical redundancy, spectral analysis.

1. INTRODUCTION

Changes (faults) can make the industrial system unsafe and less reliable. The detection and isolation (diagnosis) of fault in engineering systems is one of great practical significance. The quick and correct diagnosis of the faulty component, facilitate proper and optimal decisions on emergency and corrective actions.

Self-diagnosis of the system can be accomplished by the introduction of either analytical or hardware redundancy. In the *hardware redundancy approach*, additional physical instrumentation is introduced, sensors for instance, while in the *analytical redundancy approach*, is introduced an additional software. Analytical redundancy is less expensive, much easier to upgrade and has more potential.

Many approach have been proposed for fault detection and diagnosis. More sophisticated analytical model-based methods rely on the use of a quantitative model of the system to generate a residual sequence formed by the difference between the project output behaviour and the actual measure outcome. The residual is usually generated by parameter estimations, observers and parity relations. Also, the signal-based methods, like spectral analysis, attempt to extract useful information from the analysis of the representative signals.

A recent and complete presentation of the main approaches to fault diagnosis can be found in [Chiang, Russel and Braatz, 2001] or in [Gertler, 1998], while a review of the application of the main model-based techniques is reported in [Isermann and Ballé, 1997].

2. RESIDUAL GENERATION

Faults may be represented as unknown inputs acting on the system (*additive faults*) or as changes of some plant parameters (*multiplicative faults*). A classification of various types of faults, generally accepted by specialists, is represented in table 1 [Gertler, 1998].

Table 1

	Additive	Multiplicative
Faults	Sensor fault Actuator fault	Parametric fault (plant fault)
Noises	Sensor noise Actuator noise Plant noise	

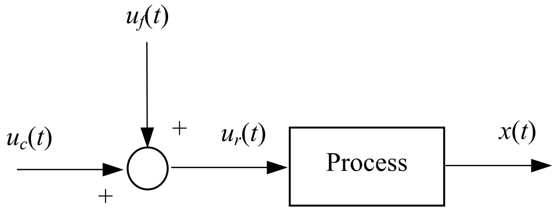

Fig. 1. Analytical modeling of a failed actuator

For example, it is possible to model the failures of actuators as additive signals. It is available the next relation:

$$u_r(t) = u_c(t) + u_f(t) \tag{1}$$

By appropriate choise of the signal $u_f(t)$, it is possible to represent various failures modes for the i^{th} actuator. In particularly, if the actuator freezes at an arbitrary position, who correspond to a_i command signal, the value for $u_f(t)$ is:

$$u_f(t) = -u_c(t) + a_i \tag{2}$$

It is necessary to say that the variables $u_c(t)$ and $x(t)$ represent the external signals, which are available for fault diagnosis purposes. The variable $u_r(t)$ is internal signal and it is inaccessible.

Figure 1 shows the generalized structure that is currently used to modeling the failed sensor. The significances of variables are:

- $u_c(t)$ - desired control input (correct signal)
- $u_f(t)$ - actuator fault
- $u_r(t)$ - actuation to plant (the real input signal)
- $x(t)$ - measured plant output (the real acquired signal)

The residuals are quantities that are nominally zero. They become nonzero in response to faults, to disturbances, to modelling error and noise (fig. 2).

For a linear system, the residual generator verify the generic relation [Gertler, 1998]:

$$r(s) = E(s)u(s) + F(s)y(s) \tag{3}$$

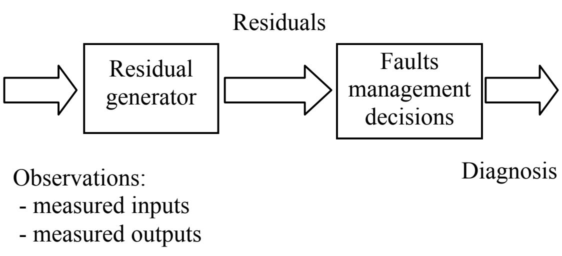

Fig. 2. The diagnosis of faulty system using the residuals.

where $u(s)$ and $y(s)$ are the measured input, respectively output of the system. $E(s)$ and $F(s)$ are transfer matrices. Equation (3) must have zero value when all the unknown inputs (faults) are zero. So:

$$E(s)u(s) + F(s)[H(s)u(s)] = 0 \tag{4}$$

where $H(s)$ is the transfer matrix of the system. Results:

$$E(s) = -F(s)H(s) \tag{5}$$

and

$$r(s) = F(s)[y(s) - H(s)u(s)] \tag{6}$$

The matrix $F(s)$ must be chosen so that the diagnostic algorithm to verify the next conditions:

- Insensitive to the disturbances
- Robust with respect to modelling error
- Sensitive with respect to faults

Ideally, the residuals must reflect only the faults. Unfortunately, the presence of disturbances, noise and modelling errors constrain the residuals to be nonzero and thus interferes with the detection of faults.

3. FAULT DETECTION AND ISOLATION

For an industrial plant, very important are the actuators and the sensors. If these are out of order, is very complicate (maybe quite so impossible) to control the process. This is the motivation for rigorous monitoring the actuators and the sensors and to inform just in time the automatic control equipment (faults management structure).

If the monitoring system give off an early warning about a fault arisen in the process, or better, about a tendency of demotion of performances, the control structure can operate for to compensate the effects.
In this case, the steps, which are proposed to be made, are the next:

- Generate an alarm signal to indicate the presence of fault in process.
- Isolation (self-acting) the fault.
- Simulate the evolution of process with fault, especially to detect the effects (errors, degradation of performances, etc).
  In this point it is necessary to analyse very careful the stability of the system.
- Elaborate the decisions, which are capable to control the process in fault conditions. Synthesis of commands in fault condition, which must assure the viability of system (possibly in a slightly degraded manner).
- Simulate the effects of each decision.
- Validate the decision with acceptable (tolerable) consequence.
- Operate, finally, on the real system (process).

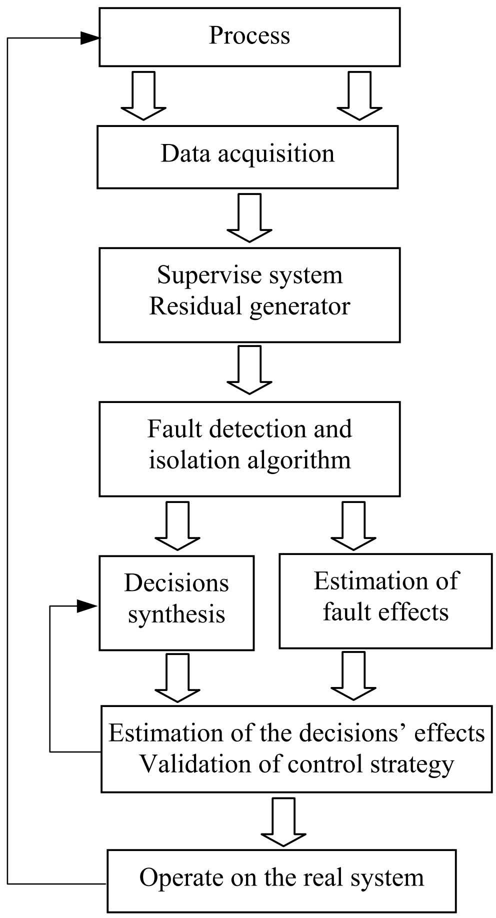

Fig. 3. The structure proposed for FDIA algorithm.

The structure of the proposed algorithm is presented in figure 3.

During the past several years, the program has successfully demonstrated several real-time Fault Detection, Isolation, and Accommodation (FDIA) techniques for different classes of faults including sensors, actuators, and components.

In order to accommodate sensor failures, a set of analytically redundant measurements, including all the variables used in the closed-loop control for overall performance, are selected.

The selected sensor data generated from the engine model, as well as from the actual engine test data, are then used to train the neural network. The redundant sensor information is processed, mixed, and regenerated to provide an estimate of the true measurement. Sensor failure is accommodated by replacing the failed sensor with the estimate for the controller. Simulation results show that the proposed sensor validation scheme can adequately identify the failed sensors and provide reasonable estimates for control purposes.

Model-based fault detection reveals actuator failures. A nominal engine model is used to provide the baseline for the normal operation of the system. An actuator fault model is developed using fault parameters. It is designed so that different fault parameters represent different types of faults of a specific actuator. An on-line estimation algorithm is used to estimate the fault parameters with the real-time input/output data. The most directly and unsophisticated way to detect and isolate the failed actuator consist to use the inverse system (fig. 4). When the problem has no exact solution, it is possible to use the pseudo-inverse method (PIM). In this case, the norm based distance between the closed loop model of the faulty system and some reference model is minimized [Staroswiecki, 2005].

Finally, a third fault detection technique, which uses the experts' heuristic knowledge, can be used to identify the known component faults that are not covered in the previous cases.

4. SPECTRAL ANALYSIS FOR FAULT DETECTION

Fourier methods are commonly used for signal analysis and system design in modern telecommunications, radar, image processing, etc. Classical Fourier methods such as the Fourier series and the Fourier integral are used for continuous time signals and systems. A more recently developed set of Fourier methods, including the discrete time Fourier transform, are extensions of basic Fourier concepts that apply to discrete time signals.

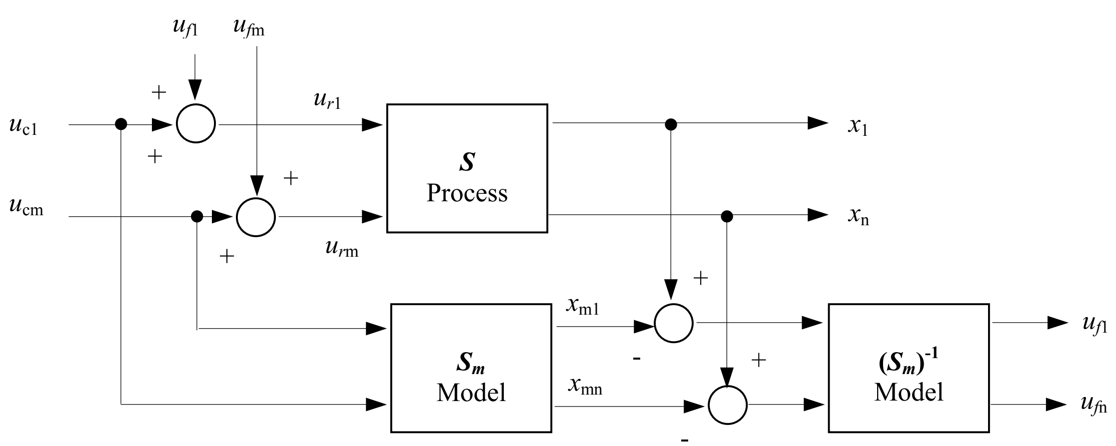

Fig. 4. Method for generates the residual vector and to detect and isolation the failed actuator.

The conditions under which a periodic signal $s(t)$ can be expanded in a Fourier series are known as the Dirichlet conditions. They require that in each period $s(t)$ has a finite number of discontinuities, a finite number of maxima and minima, and that $s(t)$ satisfies the absolute convergence criterion.

An FFT program is often used to perform spectral analysis on signals that are sampled and recorded as part of data acquisition systems. The advantage to use a spectral analysis consists in the sensitivity of this method. Any distortion of the real signal from the reference signal can be materialised by the modification of spectrum. The reference signal can be registered from the process in normal condition or can be generate on-line by the mathematical model. Each signal generate by the sensors, is periodically analysed. The presence of any strange components in his spectrum can indicate an anomalous function. If this indicator (warning signal) is correlated with the presence of components non-zero, the possibilities to detect and to isolate a fault are bigger. The structure proposed is show in fig. 5.

The method can be very useful for the test stand, when can be used also, the acoustic signals or mechanical vibration, generated by the process. Utilisation of acoustic signal has the advantage to monitoring the process without physical contact.

5. APPLICATION

Fault diagnosis of electrical machines is an important application. In this case it is possible to use the both methods:

- spectral analysis of electrical currents
- spectral analysis of acoustic signals

Indeed, vibrations and current signals bear reach information about incipient defects in mechanical parts such as imbalance, bearings, impacts, etc. [Benko *et al*., 2005]. An exemple, generated by simulation, is represented in fig. 6, 7, 8 and 9.

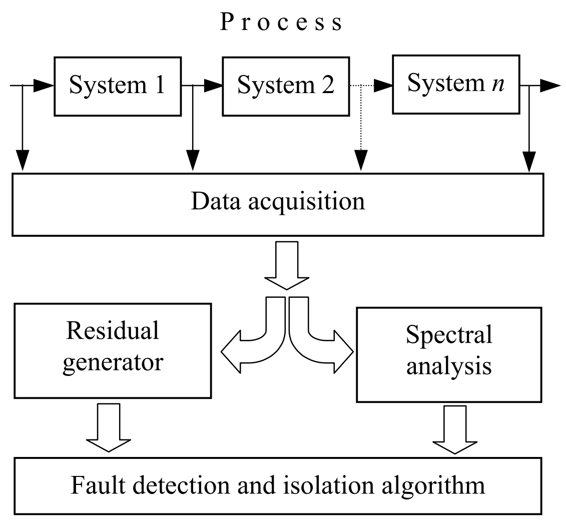

Fig. 5. Fault detection using spectral analysis.

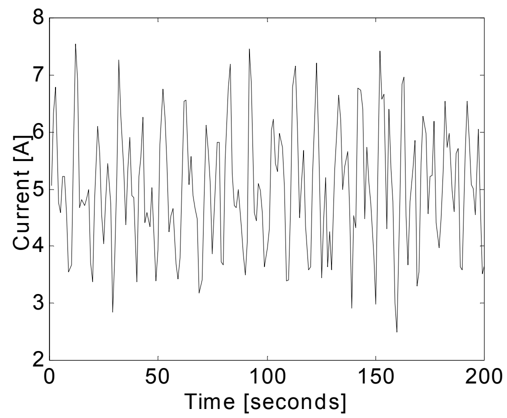

Fig. 6. The normal form for current in motor.

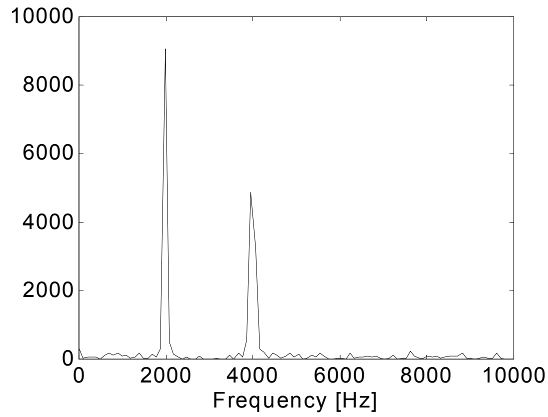

Fig. 7. The typical spectrum in normal case.

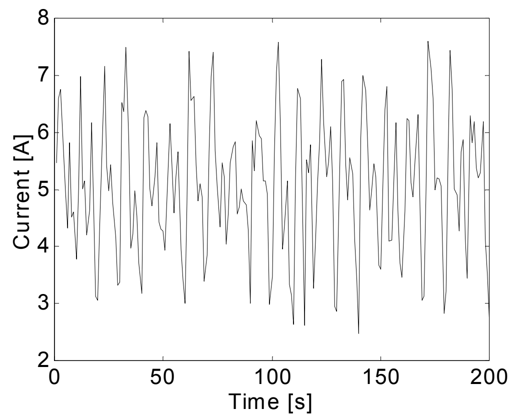

Fig. 8. The current in fault condition.

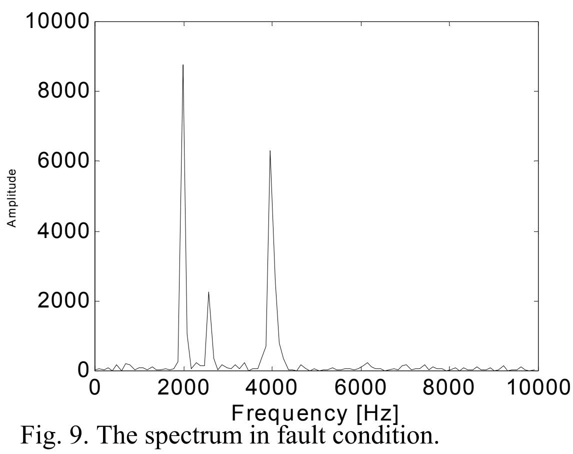

Fig. 9. The spectrum in fault condition.

6. CONCLUSIONS

In this work, spectral signal analyses are employed in fault detection and isolation scheme. The procedure was applied to detect the presence of fault in process and suppose the processing in frequency domain of the data acquisition, which represent the known commands and the actual measure outcome.

The approach has been applied to electrical motor and the results show that the fault detection scheme designed can detect incipient faults. The technique was tested by simulation and the results are good.

Also, the method can be used at test stand for electrical motor. With the necessary precautions, the processed signal can be acquisited with acoustic sensors (microphones). So, it is possible to test motorcar, where the mechanical faults (imbalance, bearings, impacts) are dominants.

Also, the method can be used in medicine, to analyse the ECG and EEG signals for non-invasive diagnosis.

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