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Signal-based diagnostic algorithms integrating model validity in the decision

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Abstract

Signal analysis can be used to perform diagnosis: features that define the representation space are extracted with a processing technique. Diagnosis consists in mapping the representation space into fault indicators easily interpreted by operators. This paper proposes two main ideas. Firstly, a limited number of realisations of one signal is considered offline to define the pattern in the representation space. Secondly, the confidence that can be attached to the pattern when the diagnostic decision is computed is taken into account. The diagnostic decision is based on multicriteria fuzzy decision-making: it aggregates the pattern validity and the similarity of the current signal features to this pattern. The proposed methodology is well adapted to FDI of multiple faults. It is illustrated with a STFT for feature generation and gives very encouraging results when applied to industrial data recorded from a roughing mill in the metal industry.

Keywords: Change detection; FDI; Fuzzy decision-making; STFT; Vibration monitoring

1. Introduction

The safety of critical systems such as aircrafts, refineries, or nuclear plants must meet strict security requirements during normal operation while assuring minimal performances in the event of malfunctions in actuators, sensors or other components of the process. Other less critical systems must also meet performance requirements to guarantee economic profits. As a consequence, fault detection and isolation (FDI) has gained increasing attention in order to enhance the safety and reliability of complex systems.

Signal processing is one way to achieve FDI. Many approaches have been proposed (Basseville & Nikiforov, 1993; Bolaers, Dron, & Rasolofondraibe, 2004; Isermann, 2006). Let x be a digital signal, and x_j a realisation defined with a vector of samples $[x_j(1), \ldots, x_j(N)]$. A processing method is applied to this realisation, the result of which is a vector of real numbers known as features $frt_j = [frt_j^1, \ldots, frt_j^m]$. These features define the representation space. Diagnosis consists in mapping the representation space into fault indicators. It is basically a decision problem, which requires a distance measure or similarity measure in the representation space and a decision rule.

Time analysis is based on features such as the signal mean μ_{x_j} and/or the standard deviation σ_{x_j}. Tests capable of detecting changes in the mean and/or the standard deviation of a signal are very common (Basseville & Nikiforov, 1993). It has also been shown experimentally that rotating machines or mechanical structures present particular spectral contents when unexpected vibrations appear (Eltabach, Charara, & Zein, 2004; Fagarasan, Lesecq, Taleb, Gentil, & Stüecher, 2004). Thus, changes in the spectrum contents $S_{x_j}(f)$ are also of interest for diagnostic purposes. These changes in the spectrum can be detected using time–frequency representations (Boashash, 2003; Flandrin, 1999; Martin, 2005). The Fourier transform of a weighted epoch of raw data (also called Short-Time Fourier Transform, STFT, or Windowed Fourier Transform) is particularly well-adapted when considering vibration detection in real-time. Its popularity is due to its

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easy interpretation, closely related to a local FFT analysis. In this case, the features consist in the various powers $S_{x_j}(f_k)$ computed at frequency f_k.

Although well-known among experts, these methods remain difficult to implement in an industrial context. The main difficulty is due to the large number of components to diagnose in such an installation (from several tens to several hundreds) resulting in a large number of signals to be soundly. On such complex installations, several similar components are usually found (for example several motors of comparable power). Therefore, it is tempting to extrapolate the analysis made for one component to the similar ones. Nevertheless, the extrapolation decreases the accuracy of the diagnosis. Moreover, an industrial plant is not always functioning in the same conditions. Particularly, the operating point changes with the production requirements. These changes can modify the signal features and must not be confused with frequency changes due to faults.

Industrial partners strongly expect a single indicator for each component, exhibiting its state in real time. Furthermore, this indicator must be easily interpreted and tuned by operators that monitor the plant, which is not the case for instance of a spectrogram. The semantic of this indicator must be "the component seems/does not seem to be in normal state". If fault isolation is required (when possible), an indicator must be attached to each fault mode F_i of the component with the meaning "the component is subject to fault F_i". With single indicators, operators can focus on a component that starts malfunctioning. When the occurrence of a fault is beyond any doubt, they can decide either to stop the component or to call the maintenance service.

The ideas proposed in this paper try to answer the industrial implementation difficulties that have been set out above. The first proposal considers that a limited number of p realisations of signal x^R is available:

$$x_1^{\mathbf{R}} = [x_1^R(1), \ldots, x_1^R(N_1)]^{\mathrm{T}},$$
$$x_p^{\mathbf{R}} = [x_p^R(1), \ldots, x_p^R(N_p)]^{\mathrm{T}}. \quad (1)$$

In Eq. (1), the index **R** stands for *Reference*. These signals may have been acquired at different times or issued from various similar components. They are analysed offline during a learning phase. The p realisations are considered equally representative of a typical behaviour: they are *prototypes* either of the system normal behaviour or of a known fault mode F_i. N_1 (respectively N_P) is the number of (time) samples of signal x_1^{R} (respectively x_p^{R}). Features are computed from these realisations. Afterwards, *patterns* representative of the different functioning modes have to be defined in the representation space (Fig. 1). The simplest case corresponds to the normal/abnormal modes discrimination (fault detection); the most interesting one corresponds to the discrimination between the normal mode and various fault modes (fault isolation). When a new realisation of this signal is acquired and processed online during plant operation, it is defined as the *current signal* $\boldsymbol{x}^C$. The *similarity* SM_i of the $\boldsymbol{x}^C$ features to the pattern has to be evaluated in the representation space.

The second proposal takes into account the confidence that is attached to the pattern, to make the diagnostic decision. This confidence is named *A Priori Model Validity APV*. In this paper, it is proposed to determine this confidence by measuring the dispersion of the various prototype features in the representation space. This confidence evaluation is part of the learning phase and it is achieved offline. During plant operation and online diagnosis, the *A Priori Model Validity* can be modified to reflect changes in experimental conditions. This paper focuses on changes in the operating point which result in an *A Posteriori Model Validity PPV*.

The paper is organised as follows. Section 2 presents the proposed general methodology after some reminders on fuzzy decision-making that is the basic tool used to make the diagnostic decisions. Section 3 explains how the methodology

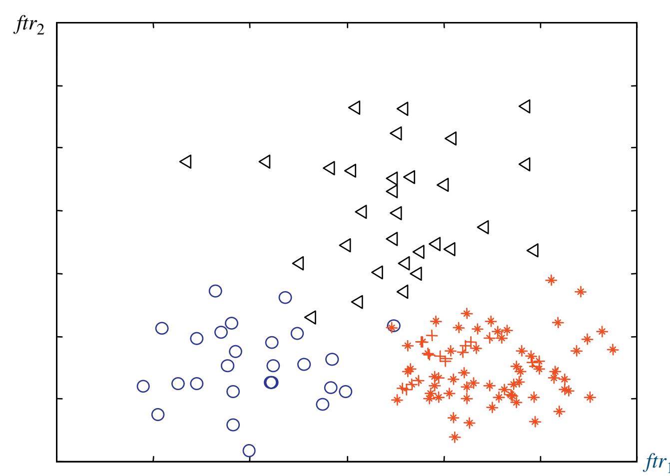

Fig. 1. Representation space with two features, three functioning modes and several prototypes for each mode.

Table 1
Notations

$\boldsymbol{x}^C$	Current signal represented by a vector of N samples acquired online, whose features are used for diagnosis
$\boldsymbol{x}_j^{\mathbf{R}}$	jth realization of the reference signal, represented by a vector of N_j samples whose features are used for pattern design
μ_{x_j}	Mean of signal x_j
σ_{x_j}	Standard deviation of signal x_j
$S_{x_j}(f_k)$	Spectrum of signal x_j at frequency f_k
FD_i	Indicator in [0, 1] for the confidence in the fault mode F_i. FD_0 represents the confidence in the unfaulty behaviour F_0
SM_i	Indicator in [0, 1] for the similarity between $\boldsymbol{x}^C$ features and the pattern of F_i
APV_i	Indicator in [0, 1] for the a priori confidence in the design of the pattern of F_i
PPV_i	Indicator in [0, 1] for the online confidence in the pattern of F_i
$\boldsymbol{OP}^R$	Vector of coordinates OP_i^R representing the reference operating point of the plant; $\boldsymbol{x}_j^{\mathbf{R}}$ is acquired around this operating point
$\boldsymbol{OP}$	Vector of coordinates OP_i representing the current operating point; $\boldsymbol{x}^C$ is acquired around this current operating point