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Interacting multiple-models, state augmented Particle Filtering for fault diagnostics

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ABSTRACT

Particle Filtering (PF) is a model-based, filtering technique, which has drawn the attention of the Prognostic and Health Management (PHM) community due to its applicability to nonlinear models with non-additive and non-Gaussian noise. When multiple physical models can describe the evolution of the degradation of a component, the PF approach can be based on Multiple Swarms (MS) of particles, each one evolving according to a different model, from which to select the most accurate a posteriori distribution. However, MS are highly computational demanding due to the large number of particles to simulate. In this work, to tackle the problem we have developed a PF approach based on the introduction of an augmented discrete state identifying the physical model describing the component evolution, which allows to detect the occurrence of abnormal conditions and identifying the degradation mechanism causing it. A crack growth degradation problem has been considered to prove the effectiveness of the proposed method in the detection of the crack initiation and the identification of the occurring degradation mechanism. The comparison of the obtained results with that of a literature MS method and of an empirical statistical test has shown that the proposed method provides both an early detection of the crack initiation, and an accurate and early identification of the degradation mechanism. A reduction of the computational cost is also achieved.

1. Introduction

In recent years, the development of relatively affordable on-line monitoring technology has yielded a growing interest in dynamic maintenance paradigms such as Condition-Based Maintenance (CBM) [25]. This is based on tracking the health conditions of the monitored equipment and, on this basis, making maintenance decisions. For this, two fundamental issues are (i) *detection*, i.e., the recognition of a deviation from the normal operating conditions; (ii) *isolation* or *diagnostics*, i.e., the characterization of the abnormal state of the system.

In principle, reliable Fault Detection and Isolation (FDI) allows identifying problems at an early stage, thus performing only strictly necessary maintenance actions, to anticipate failures. This avoids the danger of interrupting operations and possibly introducing malfunctions due to errors of maintenance operators.

The appealing potential of CBM for improving maintenance performance has boosted research and industry efforts in FDI techniques, as witnessed by the considerable amount of related literature (see [5,12,22–24,45–47] for surveys). These techniques may be divided into two main categories: data-driven methods, which resort to field data to build empirical degradation models (e.g., Artificial Neural Network (ANN, [6,50]), Support Vector Machine (SVM, [20]), Local Gaussian Regression (LGR, [33,42])), and model-based approaches, which utilize mathematical models to describe the degradation mechanism. In both cases, the detection of a change in the component state and the consequent diagnosis are based on the comparison between the output of the model and the data collected from the operating system.

With regards to the model-based approaches, a number of algorithms have been successfully applied to FDI such as reversible jump Markov Chain Monte Carlo (MCMC, [2,18,53]), parity space equations [16] and others techniques surveyed by some FDI literature review works [12], [22,23]. In particular, a variety of filtering algorithms have been developed to tackle FDI problems, which use discretized differential equations to describe the degradation evolution and stochastic noises to take into account the

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associated aleatory uncertainty. For example, Kalman Filter (KF) has been adopted to detect incidents on freeways [49] and to set a CBM policy on turbine blades affected by creep [4].

However, KF suffers from a limited applicability due to the stringent hypotheses of model linearity and Gaussian noise, which are often not compatible with practical FDI issues. Thus, some generalizations of KF, such as Extended Kalman Filter (EKF, [35,36]) and Unscented Kalman Filter (UFK, [27]), have been proposed. Nonetheless, there are still situations where these filtering approaches fail, due to high nonlinearity and for non-Gaussianity.

In this context, Particle Filtering (PF) has proven to be a robust technique [3,14], for tackling realistic FDI problems [51,52]. In particular, PF has been adopted for FDI within the Multi-Model (MM) systems framework, where the description of the possible component abnormal evolutions relies on a set of models [28]. In this setting, detection aims at identifying when the component starts to leave the nominal mode, whereas diagnostics consists in selecting the model that best fits its current behavior.

Interesting applications of PF to FDI in MM systems have been proposed in [1,10], where multiple swarms of particles are contemporaneously simulated, following all alternative models. FDI is, then, based on Log-Likelihood Ratio (LLR) tests on the recorded measurements to estimate for every swarm of particles the probability of being from the right model. However, these methods are computationally burdensome and memory demanding, as they require tracing a large number of particles.

Alternatively, an approach based on the augmentation of the state vector with a variable indicating whether the component is in normal or abnormal conditions has been propounded in [29,38,44,48]. This approach can be considered as a generalization of the Interacting Multiple Model (IMM) [19,31] algorithm by means of PF. The choice among the possible alternative conditions of the system is then taken based on the marginal distribution of the added variable. This allows the filter to automatically lead the particles to follow the right model, by the recorded measurements which force the state vector to modify the value of the added variable. In particular, such variable is chosen continuous in [29], which proposes an ensemble of Monte Carlo adaptive filters, and uses the LLR tests to make the FDI decision. On the contrary, Boolean variables indicating the component state are used in [38,44], where explicit models with associated probabilities of occurrence are assumed to be known, and used to compel the particles to evolve according to the different models. Then, the measurements acquired at the updating steps will favor the particles evolving according to the correct model. A further work discussing the augmentation of the state vector with a discrete variable representing the component state is [48]. However, notice that, this work, as well as that in [38] which investigates the potential of such algorithms, has addressed case studies with only two models, additive Gaussian noise, and abnormal conditions where a sharp and abrupt jump in the measured variables is observed. These conditions are rarely verified in practice, when the fault detection and diagnosis concerns a gradually degrading industrial component [11].

In the context of the Interacting Multiple Model systems based on PF, the novelty of the present work consists in the application of the method to a diagnostic problem, whereas previous applications were focusing on the problem of detecting abnormal conditions [1,10]. Furthermore, the proposed approach allows treating non-additive Gaussian noises and, differently to another work which considers only sharp degradations [48], it can be used also in case of gradually evolving degradation processes. An additional contribution of the paper is the comparison of different techniques such as augmented state PF, the LLR-based approach (e.g., [10]) and an intuitive approach based on statistical hypothesis tests [26]. Finally, the influence of the model parameters such as transition matrix entries and measurement error on the IMM PF diagnostic performance is investigated in order to provide hints on the parameters setting.

For the comparison, a case study is considered regarding a non-linear crack growth in a structure. In particular, the following two settings have been investigated:

1) There are only two models available, one for normal conditions and the other for degradation; hence, in this case the detection and diagnosis coincide. This setting allows us to compare the performance of our approach with that of other works of literature (e.g., [38,44]).
2) The component behavior is described by three models, the two of the previous setting and one additional model describing a different degradation mechanism leading to a different evolution of the crack growth. This allows evaluating the diagnostic capability of the proposed approach, i.e., its ability of selecting the right degradation mechanism.

The remainder of the paper is organized as follows. In Section 2, a general description of the Multi Model setting is presented, with a focus on the case study considered in this work. In Section 3, basics of Particle Filtering are recalled for completeness. Section 4 summarizes the characteristics of the PF-based techniques proposed in the literature to address FDI in Multi Model systems, and describes the particular FDI technique based on the augmented state vector. In Section 5 the application on a simulated but realistic, case study of crack growth is presented. In Section 6 conclusions are drawn and further developments discussed.

2. Multi model system

A Multi Model system is defined as a system which cannot be described by the same model during its entire life; on the contrary, the description of its evolution requires a set of M models, each one capturing different behaviors of the system in different situations or phases. Thus, a set of M state equations are proposed to describe the different evolutions, which can be divided into two main classes:

N models describing the component operation in normal conditions $m_{n_1}, \ \dots, \ , m_{n_N}$:

$$\begin{aligned} &m_{n_1}\colon \ \boldsymbol{x}_k = \boldsymbol{f}_{k-1}^{n_1}\left(\boldsymbol{x}_{k-1}, \ \boldsymbol{\omega}_{k-1}^{n_1}\right) \\ &\dots \\ &m_{n_N}\colon \ \boldsymbol{x}_k = \boldsymbol{f}_{k-1}^{n_N}\left(\boldsymbol{x}_{k-1}, \ \boldsymbol{\omega}_{k-1}^{n_N}\right) \end{aligned} \tag{1a}$$

D models describing the operation of the component which is degrading according to one of the possible D degradation mechanisms $m_{d_1}, \ \dots, m_{d_D}$ which it can be subjected to

$$\begin{aligned} &m_{d_1}\colon \ \boldsymbol{x}_k = \boldsymbol{f}_{k-1}^{d_1}\left(\boldsymbol{x}_{k-1}, \ \boldsymbol{\omega}_{k-1}^{d_1}\right) \\ &\dots \\ &m_{d_F}\colon \ \boldsymbol{x}_k = \boldsymbol{f}_{k-1}^{d_D}\left(\boldsymbol{x}_{k-1}, \ \boldsymbol{\omega}_{k-1}^{d_D}\right) \end{aligned} \tag{1b}$$

where $N+D=M$, $\boldsymbol{x_k}$ represents the state vector at time t_k, and $\boldsymbol{\omega}_{k-1}$ is the noise at the previous time step, t_{k-1}, which defines the aleatory uncertainty in the evolution of the process. In this work, we assume that the process noise distribution is known, although in real applications it must be inferred from experimental data or retrieved from expert knowledge. The interested reader may refer to [21] for a particle filtering-based technique that allows the joint estimation of the state vector and the unknown parameters of the noise distributions.

A further assumption is that the state $\boldsymbol{x}_k$ cannot be precisely measured, and the knowledge about its value is affected by