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Fatigue crack growth estimation by relevance vector machine

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ABSTRACT

The investigation of damage propagation mechanisms on a selected safety–critical component or structure requires the quantification of its remaining useful life (RUL) to verify until when it can continue performing the required function. In this work, a relevance vector machine (RVM), that is a Bayesian elaboration of support vector machine (SVM), automatically selects a low number of significant basis functions, called relevant vectors (RVs), for degradation model identification, degradation state regression and RUL estimation. In particular, RVM capabilities are exploited to provide estimates of the RUL of a component undergoing crack growth, within an original combination of data-driven and model-based approaches to prognostics. The application to a case study shows that the proposed approach compares well to other methods (the model-based Bayesian approach of particle filtering and the data-driven fuzzy similarity-based approach) with respect to computational demand, data requirements, accuracy and that its Bayesian setting allows representing and propagating the uncertainty in the estimates.

1. Introduction

1.1. Motivation

Equipment degradation and unexpected failures impact the three key elements of production competitiveness, i.e., safety, cost and quality. In safety–critical applications, e.g., those of the aerospace, process and nuclear industries, it is even more important to rely upon well-maintained components in order to reduce downtime for the sake of plant safety and overall performance efficiency. Since often machines go through degradation before failure, monitoring and predicting the trend of their degradation and condition may allow correction before failure.

Indeed, when the conditions of a component or structure can be monitored, maintenance can be planned dynamically (Marseguerra, Zio, & Podofillini, 2002; Williams, Davies, & Drake, 1994). By predicting the future evolution of the degradation state of the component or structure, it is possible to verify whether it can continue performing the required function and, in case it cannot, estimate the remaining useful life (RUL), i.e., the time remaining before it can no longer perform its function (Jardine, Lin, & Banjevic, 2006). In practice, the estimate of the RUL may be difficult to obtain because the degradation state may not be directly observable and/or the measurements may be affected by noise and disturbances.

Approaches to prognostics for failure prediction can be categorized broadly into model-based and data-driven (Chiang, Russel, & Braatz, 2001).

1.2. Model-based approaches

Model-based prognostics attempts to set up physical models of the component or structure for the estimation of the RUL. Uncertainty due to the assumptions and simplifications of the adopted models may pose limitations to this approach. Many researchers have focused on the problem of building exhaustive models of deteriorating components and structures to implement model-based prognostic tools. Markov and semi-Markov models have been widely exploited for achieving analytical results (Baruah & Chinnam, 2005; Bérenguer, Grall, & Castanier, 2000; Dong & He, 2007; Grall, Bérenguer, & Chu, 1998; Hontelez, Burger, & Wijnmalen, 1996; Kopnov, 1999; Lam & Yeh, 1994; Samanta, Vesely, Hsu, & Subudly, 1991; Yeh, 1997). On the basis of these models, several approaches have been proposed to analyze reliability-based and condition-based maintenance policies (Castanier, Bérenguer, & Grall, 2002; Chen & Trivedi, 2005; Pulkkinen & Uryas'ev, 1992; Vlok, Coetzee, Banjevic, Jardine, & Makis, 2002).

The most promising approaches rely on Bayesian methods to combine a prior distribution of the unknown degradation states with the likelihood of the observations collected, to build a posterior distribution (Caesarendra, Niu, & Yang, 2010; Doucet, 1998; Doucet, de Freitas, & Gordon, 2001). In this setting, the estimation method most frequently used in practice is the Kalman filter, which is optimal for linear state space models and independent,

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additive Gaussian noises (Anderson & Moore, 1979). In this case, the posterior distributions are also Gaussian and computed exactly, without approximations. However, in most realistic cases the dynamics of degradation is non linear and/or the associated noises are non-Gaussian. Various approximate methods can be proposed to tackle these cases, e.g., the analytical approximations of the extended Kalman (EKF) and the Gaussian-sum filters and the numerical approximations of the grid-based filters (Anderson & Moore, 1979). Recently, Monte Carlo sampling methods are gaining popularity for their flexibility and ease of design (Kitagawa, 1987). These methods go under the name of particle filtering because the continuous distributions of interest are approximated by a discrete set of weighed particles, where each particle represents a random trajectory of evolution in the state space and the weight is the probability of the trajectory (Cadini, Zio, & Avram, 2009; Djuric et al., 2003; Doucet, Godsill, & Andreu, 2000).

1.3. Data-driven approaches

Data-driven techniques utilize monitored operational data related to system health. They can be beneficial when understanding of first principles of system operation is not straightforward or when the system is so complex that developing an accurate model is prohibitively expensive.

Data-driven techniques can be divided into two categories: statistical techniques (regression methods, ARMA models, etc.) and artificial intelligence (AI) techniques (neural networks (NNs), fuzzy systems (FSs), etc.). The most direct data-driven techniques for RUL estimation attempts at fitting available data of component or structure degradation by regression models and then extrapolating the evolution up to failure. However, in practice, the component or structure degradation history available may be short and incomplete, and extrapolation may lead to large errors (Yan, Koç, & Lee, 2004).

With respect to AI techniques, the most commonly used prediction methods are based on NNs (Barlett & Uhrig, 1992; Peel, 2008; Santosh, Srivastava, Sanyasi Rao, Gosh, & Kushwaha, 2009). For prognostic tasks, promising methods are recurrent NNs (Campolucci, Uncini, Piazza, & Rao, 1999; More & Deo, 2003), Neuro-Fuzzy systems (Tran, Yang, & Tan, 2009; Wang, Goldnaraghi, & Ismail, 2004) and support vector machines (SVMs) Sotiris & Pecht, 2007. In spite of the recognized potential of empirical, data-driven techniques, limitations still exist for their use in safety–critical applications, e.g., in nuclear technology, because of the lack of a systematic approach for selecting the structure and parameters of the models and their black-box character which limits intuition with respect to the understanding of their performance (Wang, Yu, Siegel, & Lee, 2008).

1.4. A combined model-based and data-driven approach

In the attempt to benefit from specific advantages of data-driven and model-based approaches, in this paper we propose a novel approach which combines relevance vector machine (RVM) and model fitting.

RVM is a Bayesian framework, of same functional form as SVM (Drucker, Burges, Kaufman, Smola, & Vapnik, 1997), for obtaining sparse solutions to regression and classification tasks utilizing models linear in the parameters (Fletcher, 2008; Tipping, 2001). The key feature is that it offers good generalization performance through sparse predictors, which contain relatively few non-zero basis functions, the so called relevant vectors (RVs). The majority of parameters are automatically set to zero during the learning process, giving a procedure that is extremely effective at discerning those basis functions which are relevant for making good predictions and avoiding over-fitting (Tipping, 2001). Then, a model is fitted to the selected RVs, to anticipate operational conditions and predict the future states of the process under study. In the case of interest in this work, this modeling scheme is used to provide estimates of the RUL of a component or structure undergoing degradation.

The combined approach has the potential to improve conventional methods, which are either purely data-driven methods not incorporating any physics of the process into the computation or solely model-based approaches which cannot accommodate for un-modeled effects and can diverge quickly in the presence of unanticipated operating conditions. Furthermore, the Bayesian approach underpinning RVM is well suited to handle uncertainty since it stands on probability distributions over both parameters and variables, and integrates out the nuisance terms (Caesarendra, Widodo, & Yang, 2010; Fletcher, 2008; Tipping, 2001).

The applicative focus of the present paper is the estimation of the RUL of an equipment subject to a non-linear fatigue crack growth process, typical for a certain class of industrial and structural components (Bolotin, Babkin, & Belousov, 1998; Myotyri, Pulkkinen, & Simola, 2006; Oswald & Schueller, 1984; Sobezyk & Spencer, 1992), on the basis of measurements of its degradation state taken at predefined inspection times (which are likely to be only few in practice due to the fact that the lower the number of measurements, the lower the computational time and the cost associated to the inspection procedures).

The paper contents are structured as follows. Section 2 contains the description of the approach at the basis of the RUL estimation, with an overview of the RVM framework. Section 3 presents the dynamic model of fatigue crack growth. In Section 4, the results of the application of the approach to a case study are presented, and an evaluation of the performance evaluation of the prognostic algorithm is given. Finally, some conclusions on the advantages and limitations of the approach here propounded are given in Section 5.

2. Methodology

Starting from time $t = 1$ throughout the time horizon of observation T, it is assumed that J successive measurements f_j, $j = 1,2,\dots,J$ are taken at predefined inspection times T_j along a degradation-to-failure trajectory developing in the component or structure under analysis. At each T_j, the RUL estimation for the degrading component or structure is performed by resorting to a combination of RVM followed by model fitting and parameter estimation onto the identified RVs. Figs. 1 and 2 show a schematic sketch and a pseudocode of the novel computational framework, with reference to degradation signal $f(t)$, respectively.

2.1. Data collection

The first step consists in extracting the feature $f(t)$ from sensor data. For simplicity of illustration, we consider a single feature as the degradation signal used for estimating the component evolution towards failure.

2.2. Degradation model development

The degradation signal $f(t)$ is monitored throughout the time horizon of observation T, starting from (discrete) time $t = 1$; inspections of the component or structure degradation state, as indicated by signal $f(t)$, are made at predefined inspection times $(T_1, T_2, T_3, \dots, T_J)$, where, computationally, $T_j - T_{j-1} = n$ is the number of discrete time steps between two successive inspections.

At each inspection time T_j, $j = 1,2,\dots,J$, the last value $f(T_j)$ is recorded and appended to the vector of the values collected at the