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Remaining Useful Life estimation for noisy degradation trends

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Abstract: In process safety and supervision, many works are based on the data driven approaches. Among them, one widely used approach is estimating the Remaining Useful Life (RUL) based on the behavior of degradation trends. In practice, these trends are very noisy because of the measurement process and environments. This paper proposes a method to extract profiles of trends based on a percentile calculation on several levels. This allows one to have a *probability density function* (pdf) of RUL with a Confidence Interval (CI) that ensures the safety margins for industrial applications. The proposed method is illustrated using a simulation example which highlights its effectiveness, comparing to the filtering methods based on discrete wavelet transform (DWT) and empirical mode decomposition (EMD) algorithms.

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1 Introduction

From an implementation perspective of fault prognosis, there are two kinds of structures: horizontal and vertical one. The vertical prognostics structure is not explicitly dependent on the diagnostics information, it uses only time, usage conditions and some measured data to predict the RUL; such as Paris law which is widely used for damage prognosis (Sankararaman et al., 2009), (Orchard and Vachtsevanos, 2007); or Proportional Hazards Model (PHM) whose structure incorporates covariates which affect the hazard rate of the system, this model has been applied in engineering reliability (Jardine et al., 1987), (Zuashkiani et al., 2006), (Zhao et al., 2010). The horizontal structure, in contrast, uses failure mode diagnosis information to make a prognosis. This is usually the more accurate method, due to the integration of the knowledge about the type of failure and its severity into the time series prediction (Byington et al., 2002). The prediction of RUL can be accomplished based on the dynamics of an index generated using physical models or data analysis, as in (Swanson et al., 2000), (Wu et al., 2007), (Bakker and Noortwijk, 2004); this index can represent the deterioration level of equipment, so called *health index* (HI). The analysis and modeling of this index remain problematic due to uncertainties, variabilities, disturbances and noises.

In the literature, most applications of fault prognosis on real systems based on a health index show that, this index is strongly noisy, so a preprocessing is necessary. In Saarela et al. (2014), RUL estimation for Air Filters at a Nuclear Power Plant is made based on differential pressures whose measurements have an important variation over time. They are modeled as the aggregation of four components: a gradual accumulation of aerosols which has a monotonous profile, the sporadic large aerosol emission whose dynamic form is steps, a seasonal variation which has wavy form and measurement errors. The identification of these components is executed due to the knowledge of asset; however, in case of complex systems, it is complicated to have a sufficient knowledge for identification. In Nguyen et al. (2014a) and (Nguyen et al., 2014b), the health index is extracted from raw measurement data of a production process in semiconductor manufacturing, it shows the presence of a strong noise. This index is then filtered by a lowpass filter and an algorithm of monotonizing. Le Son et al. (2013) applies a regression model to filter a dispersing degradation index extracted from the 2008 PHM Conference Challenge data, which is generated from a thermo-dynamical simulation model. The limit of available techniques of filtering for fault prognosis such as wavelet decomposition, lowpass filters, regression models or empirical mode decomposition (Huang et al., 1998), is that their result is only one profile, losing thus a part of information, regardless the uncertainties of data. Besides, using them requires the knowledge of the degradation form (for regression model), or stopping criterion and number of iterations for each mode (for EMD) or frequency range of the degradation (for the frequency methods).

The HI of the cited applications has a common form: a progressive trend embedded in noise. Therefore, a real health index can be considered as the synthesis of three elements: a real degradation state as a monotonic profile, disturbances as step or waves form, and noise; including

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also some aberrant values, as illustrated in Fig. 1.

In this paper, a method based on the notion of percentiles

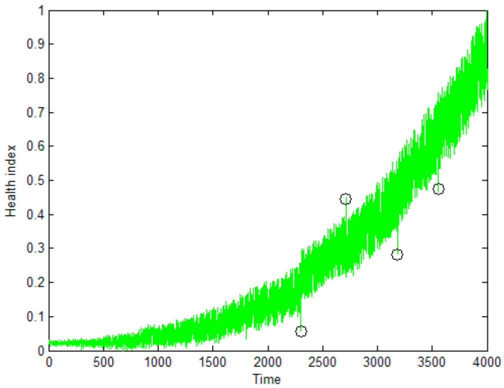

Fig. 1. A common form of real HI with aberrant values

is proposed to extract monotonic profiles from a HI. This allows to take into account the uncertainties of degradation. For training data, all of these profiles are modelled using Gamma process, then the identified parameters are used to estimate the RUL of test data. The pdf of RUL is based on the aggregation of the pdf of all the extracted profiles from testing HI to ensure a safe margin of RUL. The paper is organised as follows: section 2 describes the proposed method. An application of the proposed method is given in section 3, where the prognostic performance metrics are also implemented. Since the EMD and the wavelet decomposition techniques allow one to obtain an approximation in which the noise and disturbances are reduced, they are furthermore representative for statistical and frequency methods of preprocessing; their application are thus provided as well to highlight the effectiveness of the developed method. The conclusion is given in section 4.

2 Proposed method

2.1 Profile extraction

Given a historical health index X_t where t is the time, X_t describes a whole process of degradation, from the normal operating function to the failure. Let consider that the HI is normalized between 0 and 1, the threshold of normal operating conditions L_N and the failure threshold L_F are predefined. The interval between L_N and L_F are then divided into many levels, with a step echelon of 0.01 : $V = \{L_N, L_N + 0.01, \ldots, L_F\}$. This echelon needs to be small enough to keep the resolution of profiles explicit and detailed. However, the smaller the echelon, the longer the calculation time. Thus, 0.01 seems to be a good compromise.

Since the HI is noisy, it is possible that X_t passes through a given value at many values of t, as illustrated in Fig. 2. At each level y, $\quad y \in V$, a set of times $T_y = \{t_1, t_2, ...\}$ is obtained, in which each element t_i satisfies:

$$(X_{t_i} < y) \quad \& \quad (X_{t_i+1} \geq y) \tag{1}$$

A percentile p of each T_y is calculated, and is assigned as T_y^p. p is chosen from 25 to 75 to remove the aberrant values and keep only the relevant information; it means that there are 51 percentiles to considerate. A profile Z^p is established by:

Time	$T^p_{L_N}$	$T^p_{L_N+0.01}$	$\ldots$	$T^p_{L_F}$
Value	L_N	$L_N + 0.01$	$\ldots$	L_F

Thus, 51 profiles Z^p, $\quad p \in \{25, 26, \ldots, 75\}$ are extracted from X_t, as illustrated in Fig. 3.

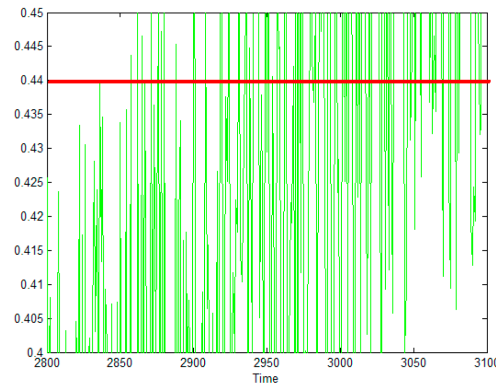

Fig. 2. A HI passes through a value many times

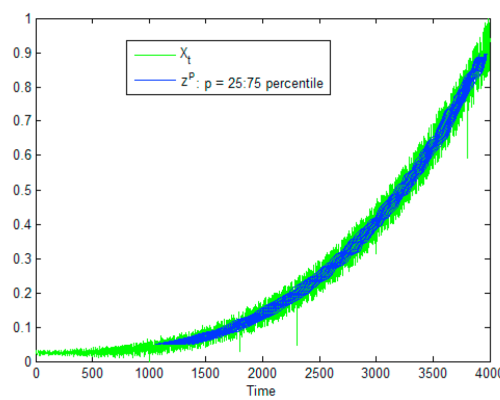

Fig. 3. Many profiles Z^p extrated from X_t

These profiles are monotonic since the HI varies progressively so that $T^p_y \leq T^p_{y+0.01}$. However, if $\exists \quad y, p$ that $T^p_y \geq T^p_{y+0.01}$, the point $(T^p_{y+0.01}, y + 0.01)$ is removed to keep Z^p monotonic.

2.2 Profile modeling

The Gamma process, detailed clearly in Noortwijk (2009), is widely used for degradation modelling as it is suitable to model gradual damage monotonically accumulating over time such as wear, crack growth, degrading health index, etc. Hence, the Gamma process can be used to model the whole Z^p.

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