Digital Signal Processing 35 (2014) 117–123

Contents lists available at ScienceDirect

Digital Signal Processing

www.elsevier.com/locate/dsp

An adaptive method for health trend prediction of rotating bearings

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ARTICLE INFO

Article history:
Available online 27 August 2014

Keywords:
Rotating bearing degradation
Adaptive prediction
Empirical mode decomposition
Self-organizing map
Confidence value

ABSTRACT

Rotating bearing degradation is a physical process that typically evolves in stages characterized by different speeds of evolution of the characteristic health indicators. Therefore, it is opportune to apply different predictive models in the different stages, with the aim of balancing accuracy and calculation complexity in light of the varying needs and constraints of the different stages. This paper proposes a condition-based adaptive trend prediction method for rotating bearings. The empirical mode decomposition–self-organizing map (EMD–SOM) method is applied to analyze vibration signals and calculate a confidence value (CV) on the bearing health state. Four different degradation stages, normal, slight degradation, severe degradation and failure, are identified by using the CV value and CV change rate. At each stage, we develop a different prediction strategy tailored to the specific degradation profile. In operation, upon recognition of the stage, the corresponding prognostics models are selected to estimate the health trend. A case study on datasets from 17 test bearings demonstrates and validates the feasibility of the proposed method. The experiment results show that the adaptive prediction method is accurate and reduces computational complexity, which can be important for online applications, especially in case of limited computing resources.

1. Introduction

Prognostics and health management (PHM) is expected to provide early detection of incipient faults and predict the progression of degradation in industrial components and systems [1–3]. Condition monitoring (CM) data, such as vibration, temperature, and pressure are collected and techniques of signal processing, feature extraction, health assessment, and RUL prediction are developed to fulfill the goals of a PHM system [4].

Rotating bearings are very common mechanical components and play an important role in a number of industrial applications. In many instances, operation of these components is in harsh working and environmental conditions, which can lead to unexpected failures [5]. In order to avoid fatal breakdowns and the consequent decrease of machinery service performance, effective component and system health management, and accurate remaining useful life (RUL) prediction are interesting solutions to implement while the roller bearing is operating.

Bearing as a common rotary machinery component, has attracted attention in both industry and academia [6–8]. The research efforts in the area of PHM for bearings have resulted in the development of various algorithms and models tailored to specific applications. With the spread of artificial intelligence and machine learning technologies, data-driven methods for estimating the RUL based on CM data have gained attention for rotating bearing health management. Heng et al. made a review of prognostics techniques and current challenges for rotating machinery prognosis [9]. Si et al. systematically reviewed the data-driven models and approaches reported in the literature in recent decades [10]. Benkedjouh et al. proposed the use of the isometric feature mapping reduction technique (ISOMAP) and support vector regression (SVR) for degradation assessment and RUL prediction [11]. Zhao Wei et al. utilized a dynamic particle filter-support vector regression method for reliability prediction [12].

Each of these prognostics models proposed in the literature has good result, however, a single prediction model may not be able to handle all situations in real practice [7,13]. Recently, researchers focus on the adaptive prognostics strategy in order to get a better prediction results. Liu points out the importance to balance the prediction efficiency and accuracy adaptively and propose an

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http://dx.doi.org/10.1016/j.dsp.2014.08.006

on-line adaptive data-driven prognostics strategy of SVR method [14]. Liao and Kottig applied a hybrid prognostics method to a battery degradation case to show the potential benefit of the hybrid approach [15]. Liao and Tian provide a framework for predicting the RUL under time-varying operating conditions [16]. Sun et al. develop a state-space-based degradation model to reduce failure prognostics uncertainty [17]. Bearing degradation has great uncertainty and the dynamic degradation states have significant influence on the PHM models effectiveness [18,19]. Although there are some adaptive methods, which can adjust their modeling by changing the parameters to follow different degradation dynamics, the results are not always satisfactory under some other circumstance [20,21]. Furthermore, the adequacy of the model for the different dynamic stages of degradation should also consider the time requisites of the application and the effects of algorithmic complexity [22,23]. In fact, in some applications CPU computing resources may be limited frequently in industrial machinery operation [24,25]. The control computers are running their own working programs and they leave not too much computing resources for PHM algorithms. Therefore, reducing the computational complexity while ensuring accuracy, can be particularly important in practice, especially for industrial systems with limited computational resources. Alternatively, a condition-based method could be developed capable of selecting the adequate prognostic models depending on the current dynamic condition state of the bearing.

Rotating bearing degradation is a physical process that typically evolves dynamically in stages characterized by different speeds of evolution of the characteristic health indicators. Therefore, it is opportune to apply different predictive models in the different stages, with the aim of balancing accuracy and calculation complexity. This leads to an adaptive scheme of PHM, whereby the stages in which the degradation proceeds gracefully calls for methods with less accuracy and, therefore, less computationally demanding, whereas the stages in which the process evolves faster call for more accurate predictions but at the expense of more demanding efforts in computation. In this way, the adaptive approach can select the better algorithm according to the varying degradation stages, while avoiding the limitations of a single algorithm.

To cope with the dynamic degradation behavior of rotating bearings and choose the proper prognostics methods for life prediction, an adaptive method for health assessment and prognosis is proposed in this paper, based on the analysis of vibration signals. The original acceleration vibration signal is decomposed by empirical mode decomposition (EMD) and the useful intrinsic mode functions (IMF) are obtained. Then, the EMD energy entropy, which can reflect the actual health condition, is converted into a confidence value (CV) to assess the bearing health state, by using a SOM method. In order to dynamically select the proper prognostics models, the bearing health state is categorized into four different health stages to each of which corresponds a specific method for predicting the health trend. A case study of a bearing run-to-failure test is analyzed.

The paper is organized as follows. Section 2 describes the bearing health assessment method based on EMD energy entropy, and SOM. The bearing health state is represented by the computed CV. Section 3 presents the framework of the proposed adaptive prediction method. In Section 4, the experimental verification and results are presented with reference to the bearing run-to-failure test. The conclusion of this paper is given in Section 5.

2. Health assessment

2.1. EMD energy entropy

EMD is a powerful signal processing technique, extensively studied and applied in prognostics of rotating bearings [26]. Traditional signal processing techniques, including time-domain and frequency-domain analysis, cannot provide complete information of the vibration signals of the bearing, which possess non-stationary and non-linear characteristics. As a self-adaptive method for time-frequency analysis, EMD is here adopted to decompose the signal into a number of IMFs and the residue of the decomposition [27]. The original signal $x(t)$ is decomposed in terms of n-empirical modes as follows,

$$x(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \tag{1}$$

where $r_n(t)$ is the residual function and $c_i(t)$ are the IMFs of different frequency bands ranging from high to low.

While the roller bearing is operating under different working conditions, the energy of the signal changes with the frequency distribution. The EMD energy entropy is used to illustrate the change of energy. For a vibration signal $x(t)$, the n IMFs and the residue $r_n(t)$ are obtained by using (1): the energies of the n IMFs $E_1, E_2, \cdots, E_n$, are calculated as follows,

$$E_i = \int_{-\infty}^{+\infty} \left|c_i(t)\right|^2 dt \quad (i = 1, 2, \ldots, M) \tag{2}$$

and the corresponding EMD energy entropies are designated as,

$$H_{EN} = -\sum_{i=1}^{M} p_i \log p_i \tag{3}$$

where $p_i = E_i/E$ $(E = \sum_{i=1}^{n} E_i)$ is the percent of the energy of $c_i(t)$ in the whole signal energy. Generally, the first m IMFs containing the most of the faulty information are considered. These m most informative selected IMFs, $c_1(t), c_2(t) \cdots c_m(t)$, include different frequency components and the energy distribution in the frequency domain of the rotating bearing vibration signal can be obtained as follows,

$$\boldsymbol{T} = \begin{bmatrix} H_{EN1}(t) & H_{EN2}(t) & \cdots & H_{ENm}(t) \end{bmatrix} \tag{4}$$

2.2. Confidence value

The proposed health assessment method is presented in Fig. 1. In order to provide an assessment of the bearing health, the confidence value (CV), which ranges from zero to one, is calculated as health indicator to represent the bearing health state, with 1 indicating a perfect health condition and 0 indicating an unacceptable failure condition [28].

The CV is obtained from the EMD energy entropy through a SOM network, which provides a way of representing multi-dimensional features into a one or two-dimensional space [29]. Each neuron i of the network is represented by an n-dimensional weight vector $m_i = (m_{i1}, m_{i2}, \cdots, m_{in})^T$. The SOM is trained with data recorded during normal operation of healthy bearings. In the use of the trained SOM, for each input feature vector $\boldsymbol{T}$ there is a best matching unit (BMU), whose weight vector m_c is the closest to the input vector and can be found in the trained SOM. The distance between the input data and the weight vector of the BMU is defined as minimum quantization error (MQE), which actually quantizes how far the degradation condition is from the normal operation state [30]. The MQE can be calculated and converted into CV to represent the degradation state of the bearings as follows,

$$\mathrm{MQE} = \|\boldsymbol{T} - \boldsymbol{m}_{BMU}\| \tag{5}$$

$$\mathrm{CV} = \frac{c}{\sqrt{\mathrm{MQE}} + c} \tag{6}$$