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Condition assessment for the performance degradation of bearing based on a combinatorial feature extraction method

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ABSTRACT

Condition assessment is one of the most important techniques to realize the equipment's health management and condition based maintenance (CBM). This paper introduces a preprocessing model of the bearing using wavelet packet–empirical mode decomposition (WP-EMD) for feature extraction. Then it uses self-organization mapping (SOM) for the condition assessment of the performance degradation. To verify the superiority of the proposed method, it is compared with some traditional features, such as RMS, kurtosis, crest factor and entropy. Meanwhile, seventeen datasets from the bearing run-to-failure test are used to validate the proposed method. The analysis results from the bearing's signals with multiple faults show that the proposed assessment model can effectively indicate the degradation state and help us to estimate remaining useful life (RUL) of the bearings.

1. Introduction

Bearings are the widely used mechanical parts in rotational equipment and usually constitute a large portion of the failure accidents. In order to avoid the fatal breakdowns of the machines, the bearing defects should be detected as early as possible to prevent unexpected failure [1]. Condition based maintenance (CBM), aiming to reduce the cost of maintenance and improve the reliability, becomes an efficient strategy during these years. Prognostics of bearing has a great significance to identify the future conditions for the maintenance plans, and also benefit to reduce the production downtime, the maintenance cost, and the safety hazards [2].

Effective performance degradation assessment is still a challenging problem in academia and industries [3]. Three main approaches, including model-based, data-driven and hybrid prognostics with statistics, are commonly used [4]. The data-driven methodology is directly based on the acquired vibration signals. Although the bearing vibration signals contain very specific information about the bearing's fault conditions, it's quite difficult to detect and track the weak signals at an early stage [5]. Thus, one of the main challenges in prognostics of the bearing is how to extract the features and construct the proper health indicators from the monitoring signals.

As the vibration signals of the bearing possess non-stationary characteristic and have the weak faulty signals with strong background noise, the time–frequency methods are considered to be an effective way for extracting the features of the original data [6,7]. The algorithm based on wavelet packet decomposition (WPD) has been applied for the vibration signal analysis [8,9]. WPD, which is capable of dividing the whole time–frequency signal into many different frequency bandwidths, has received widespread attentions in these years. The energy of the wavelet packet is commonly used to identify the failure mode of the bearings [10]. Wavelet packet energy entropy, which reflects the energy change of each sub-band when the degradation occurs, is also proved to be a good recognition method in bearing fault diagnosis [11]. In recent years, another time–frequency analysis method named as empirical mode decomposition (EMD) has been more and more widely used in signal processing [12]. The signal will be decomposed into a set of intrinsic mode functions (IMF) that involves both sampling frequency and changes with the signal itself. By analyzing each IMF, the feature information of the original signal could be extracted more effectively and accurately. Some successful fault diagnosis methods based on EMD have been carried on which use energy entropy or Hilbert transform to identify the work condition and the fault patterns [13–16]. To overcome the shortcomings in EMD, an improved EMD method using Wavelet Packet Transform (WPT-EMD) are presented in fault diagnosis [17–19]. The main purpose of using WP-EMD method in those literatures is to

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get more accurate bearing fault characteristic information. WPD is used for de-noising the signal and then put the signal decomposed into each IMFs component for envelope analysis or energy characteristics extraction. Q. Liu estimated the fault frequency by using Wavelet Package Transform and Ensemble Empirical Mode Decomposition [20]. A. Santhana Raj and N. Murali used Morlet wavelet Undecimated Discrete Wavelet Transform (UDWT) de-noising and EMD method to find the characteristic frequencies of the bearing fault [21]. However, in those methods, the trend information of IMFs is not being fully utilized and single fault frequency is not enough for degradation trend analysis. More proper features for trend analysis still need to be constructed.

The progressions of those vibration based features are not monotonic during the degradation of the bearing, which makes the remaining useful life (RUL) prediction even more challenging. Health indicator is introduced for evaluating the performance of the bearing from available features. Different features are sensitive to different faults and degradation severity [22]. A proper health indicator should be applied to describe the whole progression of the degradation for condition assessment. And this is very different from the traditional failure diagnosis which basically just needs to identify different failure modes [23]. Caesarendra et al. proposed a combination method using logistic regression (LR) and relevance vector machine (RVM) to assess the state of health and predict the RUL [24]. Huang et al. estimated the degradation condition and the RUL by using a self-organizing map (SOM) and back propagation (BP) neural network [25]. Zhao Wei et al. utilized a dynamic particle filter–support vector regression method for reliability prediction [26]. With each claiming the effectiveness of the proposed method based on the experimental results on a certain data set, those methods still have some shortcomings when multiple faults occur. Usually, a specific fault data is used for training the model and a fairly good result can be obtained in diagnosis. However, it is quite impossible for us to know the specific failure mode that will occur in a real-world prognosis, especially for a long-term prediction with multiple faults occurrences. Thus, another main challenge in the bearing prognostics is how to provide an effective condition assessment to describe the development of the performance degradation and make an accurate RUL prediction for proactive maintenance.

To solve problems mentioned above, this paper presents a condition assessment approach based on the degraded signal. The main contribution concerns the utilization of the WPD and EMD technique to extract features, as well as SOM neural networks to construct health indicators achieving the performance degradation assessment and the RUL estimation. The original signals are decomposed by the WPD and the corresponding entropy features are extracted from the time series that are obtained after the wavelet coefficient reconstruction. EMD, served as a trend analysis method, is applied to extract the entropy sequences which are taken as the input vectors of the SOM network. The confidence value (CV) derived from the SOM are used to illustrate the health state and estimate the RUL. To verify the superiority of the proposed method, it is compared with some traditional features. Seventeen datasets from a bearing run-to-failure test are used for assessment as well. The experimental results show that the prognostic approach of the proposed method can be severed as a powerful way to describe the evolution of the bearing degradation.

This paper is organized as follows. In Section 2, the combinatorial feature extraction method of WPD and EMD are presented. In Section 3, the proposed assessment method is described in details. Section 4 presents the results of the proposed method on the condition assessment of the performance degradation and the RUL estimation using the experiment signals. General conclusions are presented in Section 5.

2. Combination feature extraction based on WP-EMD

In the WPD analysis, the signal is filtered with the low-pass $\{h_k\}$ and the high-pass filters $\{g_k\}$ at first. Thus, WPD can decompose the full frequency-band of the signal into different frequency sub-bands and allow better time–frequency localization of the signals. For a signal $f(t) = x_0^1(t)$, the decomposition is defined as,

$$\begin{cases} x_j^{2i} = \sum_k h_k(k-2t)x_{j-1}^i(t) \\ x_j^{2i+1} = \sum_k g_k(k-2t)x_{j-1}^i(t) \end{cases} \tag{1}$$

The reconstruction process of the i-th wavelet on the j-th layer is defined as

$$x_j^i(t) = 2\left[\sum_k h(t-2k)x_{j+1}^{2i-1}(t) + \sum_k g(t-2k)x_{j+1}^{2i}(t)\right] \tag{2}$$

where $h(n)$ is the low-pass filter related to the scaling function and $g(n)$ is the high-pass filter related to the wavelet function.

The combination feature extraction uses 3-layers WPD as a preprocessor to de-noise and decompose of the collected vibration signal. Eight waveforms are obtained and designated as $x_3^1(t)x_3^2(t)\cdots x_3^8(t)$. The wavelet energy is varying over different scales depending on the input signals. We use the energy entropy to describe the change of the energy distribution. The energy and the entropy of each sub-band can be calculated as follows,

$$E_j^i(t) = \sum_{n=1}^{N}\left(x_j^i(t)^2\right) \tag{3}$$

$$S_{en} = -\sum_{i=1}^{N} p_j^i \log p_j^i \quad \left(S_{en} = 0 \text{ when } p_j^i = 0\right) \tag{4}$$

where i, j is the number of the wavelet coefficients, N is the length of the signal $x_j^i(t)$ and p_j^i is the energy probability distribution of the signal on the j-th layer, which is defined as

$$p_j^i = \frac{E_j^i(t)}{\sum_j E_j^i(t)} \tag{5}$$

After calculate each entropy of the collected vibration signals, the entropy sequences $s_{en}(t)$ in whole life time series can be obtained. As bearing operating, the entropy sequences will be degraded. To analyze the evolution of degradation more concisely, EMD is applied to extract the trend of entropy sequences.

EMD is a self-adaptive method to decompose nonlinear and non-stationary signals developed by Huang in 1998 [27]. It decomposes the signal into a number of IMFs and the residue of the decomposition. Given an input signal $x(t)$, the EMD procedure can be express as the following formulas,

$$\begin{cases} m(t) = \left(e_{\max}(t) + e_{\min}(t)\right)/2 \\ c_i(t) = x(t) - m_i(t) \\ r_i(t) = x(t) - c_i(t) \end{cases} \tag{6}$$

where $e_{\max}(t)$ and $e_{\min}(t)$ are the upper envelope and the lower envelope obtained from all the local maxima of the signal $x(t)$ using a cubic spline line. Then, take the residual $r_1(t)$ as the original signal and iterate (6). As a result, n IMFs can be obtained as follows,