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Classification of fault location and performance degradation of a roller bearing

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ABSTRACT

Effective fault location classification and especially performance degradation assessment of a roller bearing have been the subject extensive research, which can reduce costs and the nonscheduled down time. In this paper, a new fault diagnosis method based on multiple features, kernel principal component analysis (KPCA) and particle swarm optimization-support vector machine (PSO-SVM) is put forward. First, traditional features of the vibration signals in time-domain and frequency-domain are calculated, and then two types of features referred to as singular values and AR model parameters based on ensemble empirical mode decomposition (EEMD) are introduced. After that, the original feature vectors are mapped into higher dimensional space and the kernel principal components are extracted as new feature vectors, which are used as inputs to PSO-SVM. The experimental results show that the new diagnosis approach proposed in this paper can identify not only the fault locations but also the performance degradation of the roller bearing.

1. Introduction

Bearing is one of the most important elements in a rotary machine, and its degree of performance degradation influences the whole machine. Due to the discrete of the life of the roller bearing, regular maintenance often causes “insufficient maintenance” or “excess maintenance” [1,2]. Therefore, fault location classification and especially performance degradation assessment of a roller bearing have been the subject extensive research.

Nowadays, in order to reduce costs and nonscheduled down time, condition-based maintenance (CBM) has been applied extensively. To fulfill the goal of CBM, performance degradation assessment of the roller bearing should play a much more important role than the fault location identification, so the assessment of performance degradation, has received more and more attention. Xu et al. [3] proposed a neural network approach based on fuzzy cerebellar model articulation controller (FCMAC) to analyze the degree of the machine performance degradation. Yu et al. [4] proposed a simple and efficient machine fault diagnosis approach based on Gaussian mixture model (GMM), the experimental results shown that GMM can reliably identify not only the type of bearing fault location, but also the degree of the performance degradation. Hua et al. [5] proposed a long-term potential performance degradation analysis method based on a dynamic probability model to trace the potential performance degradation process. Pan [6] proposed a hybrid model for bearing performance degradation which was based on a support vector data description (SVDD) and fuzzy c-means (FCMs).

From the references mentioned above, we can find that there are two important aspects of the assessment of performance degradation accurately and automatically: feature extraction and intelligent classifier. Traditional diagnosis techniques extract features of the fault vibration signals in the time or frequency domain. However, due to the complexity of the working condition of roller bearings such as loads, speed, friction and other nonlinear factors, it is very difficult to classify the fault location and especially the degree of performance degradation of the roller bearing through extracting features in time or frequency domain

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only [7,8]. The empirical mode decomposition (EMD) method [9] is a new signal processing technique, which can decompose the nonlinear and nonstationary signals into a number of intrinsic mode functions (IMFs). It can provide the local features of the signal in both time and frequency domain and has been widely applied in fault diagnosis of roller bearings recently. By analyzing each resulting IMF component that represents the natural oscillatory mode embedded in the signal, the characteristic features of the original signal could be extracted more accurately and effectively. Based on the EMD method, Yang proposed the EMD energy entropy to the fault diagnosis [7,8]. Wang decomposed the original signal into a number of intrinsic mode functions (IMFs), which were composed as the feature vector matrix, performed the singular-value decomposition (SVD) method, the singular values of the SVD result described the characteristics of the signal in each frequency band [10]. Cheng found that the autoregressive parameters of the AR model were very sensitive to the condition variation [11]. However, the EMD method cannot reveal the signal characteristic information accurately because of the problem of mode mixing. To solve this problem occurring in EMD, ensemble empirical mode decomposition (EEMD) was presented by Wu and Huang [12], with EEMD, components with truly physical meaning can be extracted from the signal. Utilizing the advantage of EEMD, Lei proposed a EEMD-based method for fault diagnosis of rotating machinery and obtained a more precise diagnosis result for the fault location [13,14]. After the features are extracted, it is essentially a problem of pattern classification. Various intelligent classification methods such as artificial neural network (ANN) [15,16], support vector machine (SVM) [17,18], fuzzy sets theory, and expert systems have been applied to identify the condition from the roller bearing vibration signals.

In this paper, a multi-feature fusion method is presented to improve the accuracy of fault diagnosis of the roller bearing. Firstly, the traditional features extract from the vibration signal in the time-domain and frequency-domain. Secondly the nonstationary acceleration vibration signal is decomposed into a number of intrinsic mode functions (IMFs) by EEMD, whose singular values and AR model parameters are computed. Thirdly, the initial feature vectors composed of time-domain, frequency-domain, and time–frequency domain features are mapped into higher dimensional space and the kernel principal components are extracted as new feature vectors. At last, the resulting feature vectors are used as inputs to PSO-SVM to identify the fault locations and the degree of performance degradation of the roller bearing. The experimental results show that the diagnosis approach proposed in this paper has higher identification ability.

2. EMD and EEMD

EMD is a novel time–frequency analysis method developed by Huang et al. [19], which is based on the local characteristic time scale of signal, and it decomposes the complicated and nonlinear signal into a number of IMFs. Each IMF should satisfy the following definition [20]:

(1) The number of extreme and null point must be equal or at most a difference of one.
(2) At an arbitrary point, the mean of the maximum envelope and minimum envelope is zero.

However, one of the major disadvantages of EMD is the mode mixing problem, which is defined as either a single IMF contains widely disparate frequency scales, or a component of a similar frequency scale residing in different IMFs. The occurrence of mode mixing makes the decomposition to be lack of the physical uniqueness.

Ensemble empirical mode decomposition (EEMD) is an improved algorithm of EMD to reduce the mode mixing effect [13,20]. The principle of EEMD is to add independent white noise into the signal in many trials, and the added noise can be cancelled out on an average. Taking into account properties of the white noise, the problem of mode mixing can be overcome.

The EEMD algorithm can be given as follows:

1. Add a white noise series n_m with given amplitude to the original signal $x(t)$.

$$x_m(t) = x(t) + n_m(t) \tag{1}$$

where $x_m(t)$ represents the noise-added signal of the mth trial. $n_m(t)$ indicates the m-added white noise.
2. Decompose the noise-added signal $x_m(t)$ into I IMF $C_{i,m}(i = 1, 2, \ldots\ldots, I)$ using EMD method. $C_{i,m}$ represents the ith IMF of the mth decomposition.
3. Repeat steps 1 and 2, M trials with a different white noise series each time.
4. Calculate the overall average y_i of mth decomposition of the IMF.

$$y_i = \frac{1}{M}\sum_{m=1}^{M} c_{i,m} \quad i = 1, 2, \ldots, I, m = 1, 2, \ldots, M \tag{2}$$

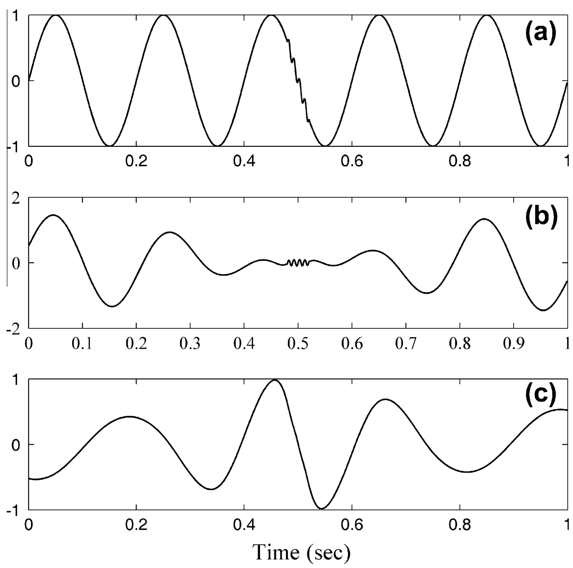

Fig. 1. The decomposition result with EMD: (a) the simulation signal, (b) IMF c_1, and (c) IMF c_2.