Measurement 59 (2015) 73–87

Contents lists available at ScienceDirect

Measurement

journal homepage: www.elsevier.com/locate/measurement

Fault diagnosis approach for rotating machinery based on dynamic model and computational intelligence

Junhong Zhang, Wenpeng Ma *, Jiewei Lin, Liang Ma, Xiaojie Jia

State Key Laboratory of Engines, Tianjin University, Tianjin 300072, China

ARTICLE INFO

Article history:
Received 13 February 2014
Received in revised form 12 September 2014
Accepted 16 September 2014
Available online 28 September 2014

Keywords:
Fault diagnosis
Rotor dynamics
Improved empirical mode decomposition
Kernel clustering
Fuzzy support vector machine

ABSTRACT

In order to achieve accurate diagnosis for rotating machinery automatically and considering that test data under actual fault conditions are rather difficult to obtain, a novel fault diagnosis strategy based on rotor dynamics and computational intelligence was proposed in this paper. Considering the nonlinear restoring force of ball bearing, the dynamic equation of a rotor–bearing system containing four typical faults was deduced with lumped mass method. Vibration responses of the system under various conditions of different rotational speeds, fault types and fault degrees were acquired. An alternative empirical mode decomposition (EMD) method improved by wavelet packet decomposition was developed to process the fault signals. Time–frequency characteristics calculated via the improved EMD as well as statistical parameters of the signal in time- and frequency-domains were extracted as fault features. Then, fuzzy support vector machine (FSVM) optimized by multi-population genetic algorithm was adopted to identify the state of the system automatically. Fault diagnosis results validate the effectiveness of the proposed approach as well as its superiority over commonly used support vector machines. The performances of different fault features and the anti-noise capability of the approach were also investigated. Results demonstrate that the proposed approach is very suitable for engineering application owing to its high accuracy and strong robustness.

1. Introduction

Rotating system is the key part of industrial equipments such as generators, motors, compressors, and aeroengines. Occurrence of fault in rotating system may cause these machines to break down or their performances to degrade, which will lead to safety risk and increase of maintenance cost. Therefore, it is significant to detect and diagnose the existence and severity of fault accurately in rotating systems during their operations.

A large number of studies on fault diagnosis of rotating machinery have been developed in recent years. They mainly focus on three aspects of the diagnostic process. One is fault mechanism with rotor dynamics that aims to reveal the effects of faults upon the responses of the system. The second is signal processing with feature extraction which provides some characteristics as indicators of faults, and the last is fault recognition that utilizes some classifiers to identify faults automatically. Diagnostic procedures may be established from one aspect or the combination of them. Sinou [1] studied the nonlinear dynamic responses of an unbalanced flexible rotor supported by ball bearings, finding that the nth Fourier components were significant when the rotor pass through the $1/n$ sub-critical and critical speeds. Patel and Darpe [2] investigated the effect of misalignment on vibration responses of two coupled rotors using Timoshenko beam elements, and found full spectra and orbit plots being

* Corresponding author. Tel.: +86 022 27407831; fax: +86 022 27407851.
E-mail address: wenpengma@tju.edu.cn (W. Ma).

http://dx.doi.org/10.1016/j.measurement.2014.09.045
0263-2241/

effective to reveal the nature of misalignment fault. Jalan and Mohanty [3] calculated the residual forces of vibrations from experimental results for a rotor bearing system subject to misalignment and unbalance, and compared these forces with the equivalent theoretical ones to detect faults, but a large number of measurement vibrations are needed. Zou et al. [4] discussed the torsional vibrations of a cracked rotor system with numerical simulation, and suggested the time–frequency features extracted by wavelet analysis as the criteria for crack identification.

However, analyses on the fault features of rotor dynamic responses under different fault conditions are mainly concentrated on frequency spectra, which are not thorough enough to distinguish faults in practical engineering since coupled-faults may have overlapped features in frequency domain. Furthermore, spectral approaches may fail to recognize faults in some practical cases involving non-stationary data. Thus many advanced signal processing methods, including blind source separation (BSS) [5], wavelet transforms (WT) [6–8], empirical mode decomposition (EMD) or Hilbert–Huang transform (HHT) [9–12], and local mean decomposition (LMD) [13], have been developed and applied to fault diagnosis of rotating systems in recent years. Among the above techniques, EMD or HHT, a powerful tool for non-linear and non-stationary time series processing, has proved effective and superior to other methods like Fourier transform and WT in the field of machinery fault diagnosis according to its adaptability and high time–frequency resolution [14]. Lei et al. [9] extracted time-domain and frequency-domain statistical parameters from the raw vibration signals, the filtered signals and the intrinsic mode functions (IMFs) of EMD as the indicators for rotating machinery faults. Wu and Chuang [10] investigated the fault characteristics of misaligned shaft in the time–frequency Hilbert spectrum as well as the marginal Hilbert spectrum of IMF envelop, and obtained some meaningful information to recognize misalignment fault. Lin [11] utilized HHT to process the acoustic emission signals of natural fatigue cracks in rotating shafts and extracted the energy percent of the IMF components as the feature of crack. Yang et al. [12] suggested EMD energy entropy of vibration signals as an accurate feature to identify bearing fault patterns. On the other hand, further development of EMD or combination with other techniques, like ensemble EMD (EEMD) [15,16] and WT–EMD [17,18], have also been studied and applied to machinery fault diagnosis aiming at eliminating the shortcomings of EMD, including mode mixing, the first IMF covering too wide a frequency range, and some signal with low-energy components being inseparable.

Though fault features have been acquired with advanced signal processing approaches, fault diagnosis yet needs the operators' decision in practical applications. This kind of diagnosis is not autonomous, nor is it always accurate because it is based on experts' experience. With the development of manufacture industry, automated intelligent diagnostic techniques that can give accurate recognition results are in great demand. Computational intelligence methods, such as artificial neural networks (ANN) [12,17], fuzzy inference systems (FIS) [9] and rough sets (RS) [19] have been reported to fulfill such task. However these approaches present some drawbacks including local optimal solution, over-fitting, requiring a relatively large number of training samples. For the above reasons, support vector machines (SVM) [20], a recently developed computational intelligence method based on statistical learning theory and structural risk minimization principle, have been employed for fault detection and diagnosis owing to its high accuracy and excellent generalization ability even when few samples are available. And many researchers proposed new kernel functions [21,22] and parameters optimization strategies [23,24] to promote the performance of SVM. Since the optimal classification hyperplane is determined by the samples on the boundary, the influences of noises or outliers that are also located in this region should be taken into account. In conventional SVM, valid samples and noises or outliers are treated as the same, thus the separating hyperplane will depart from the optimal one. Different form traditional SVM, fuzzy support vector machines (FSVM) [25] assigns each sample a fuzzy membership to reflect their importance, and thus invalid input points will contribute less with smaller memberships. FSVM has proven an effective method in face recognition [26], text categorization [27], and medical decision [28]. Therefore, FSVM is employed in this study to achieve automated fault diagnosis accurately.

Large amounts of test data from the machine under actual fault conditions are required in the above procedures. However, such data are quite difficult to obtain in industrial environment since neither artificial fault can be introduced to the equipment under operation, nor signals with all fault types and degrees can be collected. The absence of test data limits the application of the above diagnostic approaches. Enlightened by literature [29], the fault diagnosis model in this paper is established on the simulation data from a well-constructed rotor dynamic model with different fault types and degrees. And multi-domain features are extracted to fully reflect the condition of the system.

According to the above analyses, we propose a novel fault diagnosis strategy for rotating machinery including the following procedures: a rotor dynamic model is established to simulate the operations of the machinery and generate fault data. Section 2 describes the deduction of the system model and analyzes the corresponding responses under different fault conditions. Then, a series of fault features comprised of statistical characteristics of the fault signal in time- and frequency-domains as well as the IMF feature based on an improved EMD are extracted, which is illustrated in Section 3. Afterwards, a computational intelligence method combining FSVM, fuzzy clustering and genetic algorithm is adopted to recognize the fault. Section 4 presents the principle of FSVM, the means of setting appropriate fuzzy memberships to samples and the optimization process of FSVM. Section 5 gives the fault diagnosis results of the proposed approach and discusses its performance. And Section 6 is the conclusions.