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Multi-fault diagnosis for rolling element bearings based on ensemble empirical mode decomposition and optimized support vector machines

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ABSTRACT

This study presents a novel procedure based on ensemble empirical mode decomposition (EEMD) and optimized support vector machine (SVM) for multi-fault diagnosis of rolling element bearings. The vibration signal is adaptively decomposed into a number of intrinsic mode functions (IMFs) by EEMD. Two types of features, the EEMD energy entropy and singular values of the matrix whose rows are IMFs, are extracted. EEMD energy entropy is used to specify whether the bearing has faults or not. If the bearing has faults, singular values are input to multi-class SVM optimized by inter-cluster distance in the feature space (ICDSVM) to specify the fault type. The proposed method was tested on a system with an electric motor which has two rolling bearings with 8 normal working conditions and 48 fault working conditions. Five groups of experiments were done to evaluate the effectiveness of the proposed method. The results show that the proposed method outperforms other methods both mentioned in this paper and published in other literatures.

1. Introduction

With the constantly increasing level of automation in today's industry, condition monitoring and fault diagnostics methods are gaining more importance because of the need to increase reliability and decrease possible loss of production due to any unforeseen downtime resulting from damage or failure. Rolling element bearing is one of the most common components in modern rotating machinery. The failure of rolling element bearings can result in the deterioration of machine operating conditions. Therefore, it is significant to detect fast, accurately and easily the existence and severity of a fault in the bearing. Owing to vibration signals carry a great deal of information representing mechanical equipment health conditions, the use of vibration signals is quite common in the field of condition monitoring and diagnostics of rotating machinery [1–4]. The ultimate goal of vibration fault diagnosis is to set up an effective, reliable and fast identification system which can monitor the working condition of machinery and automatically specify whether it has faults or not and, if so, specify the fault type. The performance of an identification system is highly dependent on the amount of information contained within the extracted fault features and the ability of the classifier to correctly differentiate among faults [2].

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Fault features can be extracted from the vibration signals with signal processing techniques. For rolling element bearing fault detection, it is expected that a desired time–frequency analysis method has good computational efficiency, and has good resolution in both time and frequency domains. The wavelet transform (WT) has been a good choice [5,6]. However, WT suffers from the following two drawbacks. Firstly, due to the fact that WT is essentially an adjustable windowed Fourier transform, energy leakage will inevitably occur when it is used to process signals. Secondly, the appropriate base function needs to be selected in advance, and once the decomposition scales are determined, the result of WT would be the signal under a certain frequency band. Unlike WT, empirical mode decomposition (EMD) offers a different approach to signal processing and overcomes the above two deficiencies of WT since it is based on the local characteristic time scales of a signal and could self-adaptively decompose the complicated signal into some intrinsic mode functions (IMFs) [7]. IMFs represent the natural oscillatory mode embedded in the signal and work as the basis functions, which are determined by the signal itself. EMD has been widely applied in fault diagnosis of rolling element bearings [8,9]. However, an open problem of EMD is the mode mixing problem, which is a result of signal intermittency. When the problem of mode mixing occurs, an IMF can cease to have physical meaning by itself, suggesting falsely that there may be different physical processes represented in a mode [10].

In 2009, Wu and Huang [10] proposed an improved version of EMD, called ensemble EMD (EEMD). By adding finite white noise to the investigated signal, the EEMD method can eliminate the mode mixing problem of EMD automatically. Based on these merits, the EEMD has lately attracted significant attention and it has been proven to outperform EMD in decomposing vibration signals of rotating machinery [1,4,11]. Apart from using EEMD as a non-stationary signal decomposing tool, based on IMFs decomposed by EEMD many researchers extract fault features which can reveal the signal characteristic information accurately. Zhang et al. [12] extracted two types of features referred to as singular values and AR model parameters based on EEMD. And then input these features to particle swarm optimization support vector machine to diagnose faults for rolling element bearings. Ozgonenel et al. [13] investigated EEMD performance and to compared it with classical EMD for feature vector extraction. An et al. [14] use EEMD and Hilbert transform effectively extract the fault features of bearing pedestal looseness of wind turbine. Xiong et al. [15] proposed a new procedure, combining the customary HHT with a fourth-order spectral analysis tool named Kurtogram, to extract high-frequency features from several kinds of faulty signals for rotating machinery.

After feature extraction, an intelligent classifier is needed. SVM is a powerful machine learning method based on statistical learning theory and structural risk minimization principle which make it less prone to overfitting. It is generally acknowledged that SVM has a good performance in solving small sample size, nonlinear and high dimensional pattern recognition problems. It solves satisfactorily the overfitting and local optimal solution problem of artificial neural networks (ANN). Recently, SVM has been vastly applied in fault diagnosis and condition monitoring of machines [5,16–18]. However, the parameter selection of SVM is an ongoing research issue. Several techniques for parameter selection of SVM have been developed so far: trial and error procedures, grid algorithm, cross validation method, generalization error estimation and gradient descent methods, and evolutionary algorithm [19]. An indispensable step of all the parameter selection methods is that the search intervals of parameters must be determined in advance. This is a tricky task since the search intervals are problem-dependent. Many numerical experiments and past experience have indicated that the width parameter γ is the key factor in SVMs model selection when the Gaussian kernel function is selected. In literature [20], the authors used inter-cluster distances (ICD) in the feature spaces as the data separation index to choose the kernel parameters for the binary SVM. The ICD in the feature space shows the separation degree of the classes. A larger ICD implies a pair of more separated classes. They found the best kernel parameters according to the largest ICD. However, their research was mainly to select parameters for binary SVM. In this paper, a method using ICD to determine the effective search interval of kernel parameters for multi-class SVM (ICDSVM) is proposed.

In this paper, a novel hybrid method based on EEMD and ICDSVM is presented for multi-fault diagnosis of rolling element bearings. The vibration signal is adaptively decomposed into a number of IMFs by EEMD. Two types of features are extracted from IMFs. The first type feature is EEMD energy entropy which can measure the randomness of energy distribution in different IMFs of a signal. When a fault occurs in the bearing, the corresponding resonance frequency components are produced, consequently, the energy will distribute mainly in the resonance frequency band and the distribution uncertainty is relatively less, therefore, the energy entropy would reduce [21]. Hence, the EEMD energy entropy is used to specify whether the bearing has faults or not. If the bearing has faults, the second type of feature, singular value vector which is obtained by singular value decomposition (SVD) from the matrix whose rows are formed by IMFs, is input to ICDSVM to specify the fault type. Owing to singular value is the nature characteristics of matrix and own favorable stability, and has the characteristics of scale invariance and rotating invariance, it is very feasible to be the fault feature. We called this fault type classification method as EEMD–ICDSVM. The proposed hybrid method was tested on a system with an electric motor which has two rolling bearings with 8 normal working conditions and 48 different fault working conditions covering different fault locations, different fault severity levels and different loads (rotational speeds). Five groups of experiments were done and the results were compared with other methods both mentioned in this paper and published in other literatures.

The rest of the paper is organized as follows. In Section 2, the EEMD method will be introduced, while SVM optimized by ICD will be described in Section 3. In Section 4, we are going to explain the feature extraction methods and the fault diagnosis steps. Section 5 will present the experimental results. Finally, the conclusion is drawn in Section 6.