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Fault diagnosis based on dependent feature vector and probability neural network for rolling element bearings

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ABSTRACT

Rolling element bearings (REB) are crucial mechanical parts of most rotary machineries, and REB failures often cause terrible accidents and serious economic losses. Therefore, REB fault diagnosis is very important for ensuring the safe operation of rotary machineries. In previous researches on REB fault diagnosis, achieving the accurate description of faults has always been a difficult problem, which seriously restricts the reliability and accuracy of the diagnosis results. In order to improve the precision of fault description and provide strong basis for fault diagnosis, dependent feature vector (DFV) is proposed to denote the fault symptom attributes of the six REB faults in this paper, and this is a self-adaptive fault representation method which describes each fault sample according to its own characteristics. Because of its unique feature selection technique and particular structural property, DFV is excellent in fault description, and could lay a good foundation for fault diagnosis. The advantages of DFV are theoretically proved via the Euclidean distance evaluation technique. Finally, a fault diagnosis method combining DFV and probability neural network (PNN) is proposed and applied to 708 REB fault samples. The experimental results indicate that the proposed method can achieve an efficient accuracy in REB fault diagnosis.

1. Introduction

Rolling element bearings (REB) are frequently used in rotary machinery, and they are also crucial mechanical parts. REB faults not only affect the normal operation of the machine, but may also cause consequences such as production disruptions, economic loss, and even life casualties [1,2]. Therefore, the exact condition monitoring and fault diagnosis for REB play an important role in ensuring the reliable running of machinery [3,4], and the researches on REB fault diagnosis are very necessary to be developed and continuously improved [5,6].

Signal processing is a significant procedure of fault diagnosis systems, and time–frequency analysis [7], envelope analysis [8], cyclostationary analysis [9] and the combinations of them [10,11] are commonly adopted in fault diagnosis. In recent years, an advanced time–frequency analysis method called empirical mode decomposition (EMD) has become widely used in signal analysis. EMD is self-adaptive in nature and decomposes a signal on the basis of its frequency content and variation [12,13]. EMD is a powerful method for nonlinear and non-stationary signal processing [14], and the IMF components produced by this method usually possess physical meanings. EMD has been proved quite versatile in a broad range of applications in the fault diagnosis of machinery, such as gear fault diagnosis [15,16], rotor fault diagnosis [5] and REB fault diagnosis [16,17].

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Feature selection is a critical processing step designed to find the most informative feature subset, and it is an effective method to improve the classification accuracy and reduce the computational burden of the classifier [18,19]. The commonly used feature selection methods include distance evaluation technique [20], local learning-based feature selection [21], mutual information algorithm [22,23], F-score feature selection [24] and Laplacian based feature selection [25]. All of them could eliminate redundant features, and find an informative feature subset. Therefore, they could effectively improve the diagnostic accuracy and reduce the computing complexity. Feature weighting technique is another significant procedure to improve the classification accuracy, which could emphasize the contribution of the sensitive features to classification and weaken the interference of irrelevant features [26,27]. Therefore, Feature weighting is widely used in forecasting [28], classification [29] and fault diagnosis [30,31].

On the basis of feature selection methods and feature weighting techniques, this paper pays more attention to the different description ability of each feature about different samples and its different influence on the correct recognition of different samples. In order to achieve this purpose, dependent feature vector (DFV) is proposed in this paper to denote the fault symptom attributes. DFV selects the informative feature subset for each sample according to its own characteristics, and uses different feature subsets to describe different samples. So, it not only retains the most effective information for each sample, but also could reduce the differences among the samples of the same class. Then, through selecting appropriate value (*DV*) for the invalid DF, DFV significantly enlarges the difference among the different classes. Therefore, DFV could effectively enhance the compactness of the samples in the same class and the separability among different classes, achieving the accurate fault description. Moreover, the redundant information of each sample is removed to the hilt via DFV. Hence, the computing complexity and burden of feature extraction and fault identification are greatly reduced, while the fault diagnosis accuracy is also improved.

Fault classification is another key procedure. In the past few decades, support vector machine [24,28,29], artificial neural network [10] and fuzzy inference [18,30,31] are widely used and developed to identify mechanical failures. Probability neural network (PNN) [32], which needs one epoch of training and could accomplish training and classifying in an extremely short time, is proved to be very suitable for identification problems with simple feature vector [33]. In accordance with the simplicity of DFV, PNN is introduced as the classifier to realize automatic fault classification.

The purpose of this paper is to establish a fault diagnosis method based on DFV and PNN (DFV–PNN) for REB fault diagnosis. It is structured as follows: Section 2 puts forward the basic concept of DFV. The establishing method, computing method and effectiveness evaluation of DFV are described in Section 3. And in Section 4, the classifier is discussed. The experiment of REB fault diagnosis is introduced in Section 5. Finally, the conclusions of this work are summarized in Section 6.

2. The proposition of DFV

For classification problems, almost all of the traditional intelligent classification methods use the same feature vector to represent all samples. They ignore the different description ability of one feature to different samples, as well as its different influence on the correct recognition of different samples. However, humans usually deal with the same problems through another way, and they describe samples of a certain class using a unique feature vector. For example, for the classification problem of the cards in Table.1, the classification process of the traditional intelligent classification methods is showed in Fig. 1, but that of humans is showed in Fig. 2. The unique feature vector used by humans is showed in Fig. 3.

Apparently, humans use fewer features to describe each card and realize cards classification accurately. Humans emphasize the description ability differences of each feature to different cards, and select the most concise and effective feature subset for each card according to its own characteristics. Moreover, the classification way of humans spends less time than the traditional intelligent classification methods in features extraction. In order to imitate the sample description method of humans, DFV is presented in this paper, and its structure is showed in Fig. 4.

A DFV is composed of one leading feature (LF) and several dependent features (DF). For one DFV, the LF is an indispensable feature, but DF could be nonexistent. The number of DF depends on the value of LF, and it is equal to or less than the number of the different values of LF. For the situation that the values of LF are continuous, the number of DF is equal to or less than the number of the different value intervals of LF. Moreover, Every DF is a DFV. For each described object, none or only one DF is effective, and the value of LF decides whether there is an effective DF and which the effective DF is. A specific value (*DV*) is assigned to all the feature items of the ineffective DF.

Table 1
The cards.

Category	Features					
	Thickness		Shape		Color	
	Description	Value	Description	Value	Description	Value
C1	Thick	1	Round	1	Yellow	1
C2	Thin	2	Round	1	Yellow	1
C3	Thin	2	Round	1	Purple	2
C4	Thin	2	Round	1	Red	3
C5	Thin	2	Square	2	Red	3