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Reliable fault diagnosis method using ensemble fuzzy ARTMAP based on improved Bayesian belief method

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ABSTRACT

In this paper, a fuzzy ARTMAP (FAM) ensemble approach based on the improved Bayesian belief method is presented and applied to the fault diagnosis of rolling element bearings. First, by the statistical method, continuous Morlet wavelet analysis method and time series analysis method many features are extracted from the vibration signals to depict the information about the bearings. Second, with the modified distance discriminant technique some salient and sensitive features are selected. Finally, the optimal features are input into a committee of FAMs in different sequence, the output from these FAMs is combined and the combined decision is derived by the improved Bayesian belief method. The experiment results show that the proposed FAMs ensemble can reliably diagnose different fault conditions including different categories and severities, and has a better diagnosis performance compared with single FAM.

1. Introduction

Rotating machinery plays a critical role in contemporary manufacturing industry. Once they suffer from the faults, they can affect the quality of products and decrease the level of performance. To maintain the mechanical equipment early and prevent economic losses reliable and accurate fault diagnosis is indispensable. Nowadays, many signal processing methods, such as wavelet analysis [1,2], stochastic resonance techniques [3,4], have been employed to detect the machine faults at an early stage. But, these methods require a good deal of expertise to apply them successfully. Further, due to the complex, nonlinear and multi-coupling behaviors of the mechanical equipments it is also unfeasible to identify the faults through theoretic analysis and mathematical model. Therefore, there is a demand for techniques that can identify the machine faults automatically and reliably.

Recently, artificial neural networks (ANNs) have been widely used as an intelligent fault diagnosis tool to identify faulty and normal machine conditions which are treated as classification problems based on learning pattern from empirical data modeling in complex mechanical processes and systems [5]. For example, the BP, RBF and SVM models have been developed quickly and utilized to monitor and detect the machine conditions [6–8]. However, these traditional neural network methods have limitation on generalization giving rise to models that can over fit to the training samples. Subsequently, with the development of fuzzy theory [9–12] the fuzzy ARTMAP (FAM) neural network is created to solve the problem and applied to the fault diagnosis [13,14], which is an incremental and supervised network model and designed in accordance with adaptive resonance theory. Although the FAM is able to overcome the stability–plasticity dilemma [15], in real-world application, the performance of FAM is affected by the sequence of sample presentation for the off-line mode of training [16,17].

For this drawback some preprocessing procedures, known as the ordering algorithms such as min-max clustering and genetic algorithm [18,19], have been proposed for FAM. And a number of fusion techniques have been proposed for FAM to overcome this problem and improve the classification reliability. Tang employed the voting algorithm of FAM to diagnose the bearings faults [20], Loo applied the multiple FAM based on the probabilistic plurality voting strategy to medical diagnosis and classification problems [21]. But the ordering algorithm and the fusion techniques do not consider the effect of number of the training samples, in other words the diagnosis accuracy of the ordering algorithm is affect by the total number of the sample and that of these fusion techniques is affected by the number of samples in each class. To decrease the effect of the number and the sequence of the training sample, and

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to improve the diagnosis accuracy and reliability of the FAM, an improved Bayesian belief method (BBM) is used to combine multiple FAM classifiers which are off-line trained in different sequences of samples in this paper.

It is well known that feature parameters extracted from the raw vibration signals are often employed to represent the faulty information about the rotating machinery. To acquire more information about the faults, frequency domain features, wavelet grey moments and auto-regression model parameters are extracted to depict the faults in this paper. However, too many features can increase the computation burden and reduce the classification accuracy because of redundancy and irrelevance of some features. In order to improve the classification accuracy and reduce computation time, some salient features need to be selected from the original feature set. At present, lots of feature selection methods have been developed, such as conditional entropy [22], genetic algorithms [23], distance evaluation technique [24,25], distance discriminant technique [26]. Here, owing to the simplicity and reliability of the distance discrimination technique, a modified distance discriminant technique is adopted to select the optimal features from the original feature set.

In view of the above principles, a novel fault diagnosis method based on feature extraction methods, the modified distance discriminant technique and multiple FAM classifiers is proposed to diagnose the rotating machinery. The diagnostic schematic graph is shown in Fig. 1. First, through different features extraction methods some feature parameters are extracted from the raw vibration signals. Second, by the modified distance discriminant technique the optimal feature set is selected from the original feature set. Finally, multiple FAM classifiers ensemble based on the improved BBM is employed to come up with the final diagnosis results. The proposed method is applied to the fault diagnosis of rolling element bearings. The experiment results show the effectiveness of the proposed feature selection method and the superiority of the fusion of multiple FAM classifiers.

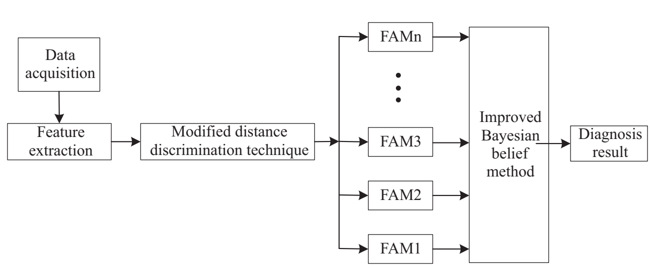

Fig. 1. Flowchart of fault diagnosis system.

2. Feature extraction and selection

2.1. Feature extraction

Feature extraction is the key step in the process of intelligent fault diagnosis. Because these extracted features can not only characterize the information relevant to the bearing conditions, but also affects the final diagnosis results. In this paper, to acquire more fault-related information many features in different symptom domains are extracted from the measured signals.

2.1.1. Frequency domain feature

Frequency-domain is another description of a signal. In Ref. [28] some novel features which can give a much fuller picture of the frequency distribution in the each band of frequencies are proposed. Supposed N points of normalized PSD, P_{xx}, of the vibration signal, P_{xx} is divided into L segments, where L is 4 in this study. The four features based on the moment estimates of power can be obtained as follows:

$$k_1=\frac{1}{N'}\sum_{N'}P_{xx}(n) \tag{1}$$

$$k_2=\frac{1}{N'-1}\sum_{N'}(P_{xx}(n)-k_1)^2 \tag{2}$$

$$k_3=\frac{1}{N'k_2^{3/2}}\sum_{N'}(P_{xx}(n)-k_1)^3 \tag{3}$$

$$k_4=\frac{1}{N'k_2^{2}}\sum_{N'}(P_{xx}(n)-k_1)^4 \tag{4}$$

where 'n' is the number of total data points, N' is the number of sample points in the lth segment.

In order to characterize the spectrum with a higher accuracy the moment estimates of frequency weighted by power are calculated by the following formulas:

$$k_5=\frac{1}{K_l}\sum_{N'}f(n)P_{xx}(n) \tag{5}$$

$$k_6=\sqrt{\frac{\sum_{N'}[(f(n)-k_5)^2P_{xx}(n)]}{K_l}} \tag{6}$$

$$k_7=\frac{1}{K_lk_6^3}\sum_{N'}[(f(n)-k_5)^3P_{xx}(n)] \tag{7}$$

$$k_8=\frac{1}{K_lk_6^4}\sum_{N'}[(f(n)-k_5)^4P_{xx}(n)] \tag{8}$$

where $f(n)$ is the corresponding frequency of $P_{xx}(n)$ and K_l is the total power in the segment. Then the total number of features extracted for each spectrum is 4×8.

2.1.2. Wavelet grey moment

To depict the fault-related information about the bearings quantitatively, the first-order continuous wavelet grey moment (WGM) [29] of vibration signal is extracted. Assuming the wavelet coefficients matrix $[W]_{M\times N}$ which can be displayed by the continuous wavelet transform (CWT) scalogram, M and N are the scales and the time of the scalogram respectively, the matrix $[W]_{M\times N}$ is divided into m parts along the scale equally and the first-order wavelet grey moment g_1 of each part can be calculated by the following the equation:

$$g_1=\frac{1}{M/m\times N}\sum_{i=1}^{M/m}\sum_{j}^{N}w_{ij}^1\sqrt{(i-1)^2+(j-1)^2} \tag{9}$$

where w_{ij} is the element of matrix$[W]_{(M/m)\times N}$. In this paper, the m is set as 16 and the wavelet function is Morlet wavelet.

2.1.3. Auto-regression (AR) model parameter

AR model is the basic time series model, which can be used as predictor. Its basic expression can be written as follows:

$$\bar{s}_n=\varphi_1s_{n-1}+\varphi_2s_{n-2}+\cdots+\varphi_rs_{n-r}=\sum_{i=1}^{r}\varphi_is_{n-i} \tag{10}$$

where $s_{n-1},s_{n-2},\dots,s_{n-r}$ are the r previous samples, $\bar{s}_n$ is the predicted sample of the signal S_n, and $\varphi_1,\varphi_2,\dots,\varphi_r$ is AR model parameters. Due to sensitiveness of these model parameters to the shape of the vibration data, these model parameters are often used as features to characterize the information about the conditions of bearings. The algorithm that these AR model parameters are obtained is described concretely in [30]. In this study, the parameter r is set as 16.

Thus, 64 features constitute the original feature set.