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Intelligent Fault Diagnosis of Rotating Machinery Using Support vector Machine and Improved ABC

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Abstract. An intelligent fault diagnosis method by means of local mean decomposition (LMD), support vector machine (SVM) and improved artificial swarm (IABC) is proposed in this paper. Firstly, the vibration signals are decomposed by means of LMD method and frequency-domain and time-domain statistical characteristics of fault information are extracted. Then, a classifier model is present, which combines IABC and SVM to improve classification accuracy. Finally, SVM model identifies different fault situations adopting the optimal features and model parameters. The experiment's result shows the effectiveness of the proposed method in fault feature extraction and fault diagnosis of rolling bearings.

Introduction

Rotating machinery serves as a core part in industrial applications, and most safety-critical rotating machinery. Once there are faults, these faults can lead to the fatal breakdown and become very costly and time-consuming. Hence, more attention is paid to fault diagnosis of rotating machinery for improving the accuracy of diagnosis and avoiding casualties and economic losses. In 2005, a novel self-adaptive time-frequency analysis method, namely local mean decomposition (LMD) was present by Smith JS [1], which could decompose a complicated multi-component fault signal into a set of product functions (PFs) self-adaptively. The LMD method has been adopted in fault diagnosis of rotating machinery recently and has shown how LMD facilitated enhanced analysis compared to empirical mode decomposition (EMD) in fault diagnosis [2]. Because fault classification is also the most important tasks in fault diagnosis, a fault classifier can be established by using many method, such as neural networks, rough set, SVM. SVM is a machine learning method developed in the mid-1990s based on statistical learning theory. It has been successfully applied in many fields including fault diagnosis of rotating machinery [3, 4].whereas, how to choose parameters optimized c and g is a difficult hen building a SVM-based diagnosis model because of the lack of relevant theoretical support. To optimize c and g, many optimization algorithms are used in fault diagnosis, such as genetic algorithm (GA) particle swarm optimization (PSO). Compared to other population-based optimization algorithms, Artificial Bee Colony (ABC) algorithm show better performance and could can be easily obtain the global solution [5, 6]. Therefore, a hybrid fault diagnosis way is proposed established on LMD, SVM and IABC. LMD is used to extract the features of the original vibration signals captured by rotating machinery to obtain more fault features. The fault classifier is constructed by SVM and optimized by IABC to determine the optimal classification results.

The next section introduces LMD and the SVM classifier. Section 3 presents an improved ABC method and an intelligent diagnosis model. Section 4 elaborates the test results and compares them with the results of other methods. In section 5, a concise conclusion is given.

Methodology

LMD Method and SVM

Local mean decomposition (LMD) is a new nonlinear and non-stationary signal analysis method proposed by Smith [7]. LMD can adaptively decompose a complex non-stationary signal into several PF (Product Function) components with instantaneous frequencies and physical meanings by using smooth local mean. Comparing with EMD, the instantaneous frequency and amplitude can be obtained by deducing analytical expressions and Hilbert transform, which can effectively compensate for the problems of over-envelope, under-envelope and endpoint effect in EMD method. Meanwhile the calculation is also simple, the calculation is small, and the fault features can be extracted accurately and comprehensively.

Usually many fault samples of rotating machinery are limited in sample number, mostly belong to small samples. The general fault diagnosis method is not good for the diagnosis of small samples, while the SVM method has a good classification effect in the case of small samples based on statistical learning theory. Therefore, this paper uses SVM to classify the fault features and optimize the parameters c and g of SVM.

Improved ABC algorithm and the Proposed Fault Diagnosis Model

Artificial Bee Colony (ABC) algorithm is proposed in the literature [5]. As a novel heuristic optimization method, the algorithm imitates the foraging behavior of bees, which has few control parameters and easy operation, and shows good characteristics compared with the GA, PSO and the differential evolutionary algorithm in the optimization of high-dimensional function.

This paper presents an intelligent fault diagnosis model based on above methods. First, the vibration signal is preprocessed by LMD, and the time-domain and the frequency-domain feature are extracted. Then, the fault classifier is built using the SVM that is optimized using the improved ABC algorithm to determine the optimal classification results. The process of the proposed model calculation is described in Figure 1, and the fault classification process is introduced as follows:

Step1: Decompose the normal vibration signals and fault vibration signals into some *PFs* respectively by LMD[8].

Step2: Extract the time-domain, the time-domain and the frequency-domain features of the signal from the first several *PFs*.

Step3: optimize c and g parameters of SVM and feature subset of vibration signals by means of imporved ABC algorithm.

Step4: train fault diagnosis model using the final output of the proposed diagnosis model.

Step5: classify the unknown fault samples to perform fault diagnosis employing the trained SVM model. The flow chart is described in Figure 1 as follow.

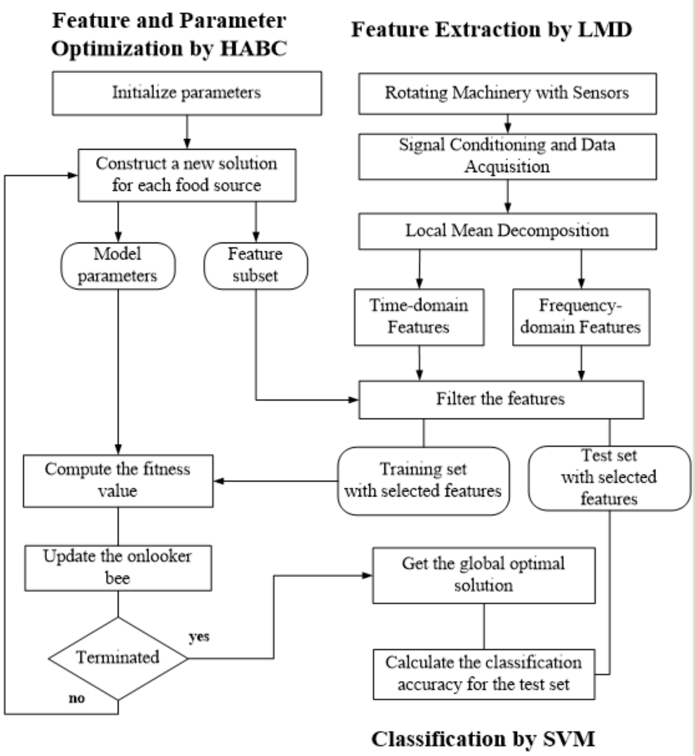

Figure 1. The flow chart of proposed method

Experiment and analysis

The proposed fault diagnosis model is employed in fault diagnosis of rolling element bearings and its effectiveness is also verified. All tests are running on a computer with a 2.10GHz Intel CPU and 4GB RAM by using Windows XP OS. The test codes is programmed using Matlab 2010a and LibSVM (version 3.12) library [8, 9].

Experimental Data

The vibration signals of rolling element bearings in experiment come from Case Western Reserve University [10]. The rolling element bearings test stand consists of a 2 hp motor supported by the test bearings, a dynamometer, and a torque transducer/encoder and control electronics. These test data include four typical operating conditions which respectively are normal condition, rolling element fault, inner raceway fault and outer raceway fault. These test data were simulated by employing electro-discharge machining with the defect sizes 0.007in, 0.014 in, 0.021 in, 0.028 in, and 0.040 in. For each kind of working condition, signals were measured under rotating speed of 1730 r/min, 1750 r/min, 1772 r/min, and 1797 r/min respectively, with a sampling frequency of 12 KHz per channel by using the accelerometer attached to the 12 o'clock position at the drive end bearing of the motor housing with magnetic bases[11].

In this study, the smallest fault diameter has been choosed for sampling test data under the shaft rotational speed of 1730 rpm (with no motor load condition).Finally, 40 vibration signals with the length of 2048 points were gathered. The frequency and waveform of the original signal can be displayed in Fig. 2. Hence, the fault diagnosis test of this paper belongs to a four-class classification task about the four operating conditions.

Performance Comparison with Different Feature Extraction Algorithms

Each raw signal is preprocessed by LMD. In Fig.3, according to the energy change with the PF number test, the first three PFs cover the most information. So, the first three PFs are selected and 20 feature parameters are extracted from each of the PFs. Therefore, 60 feature values are obtained for a data sample. The waveform and Fourier spectrum of the first three PFs of four fault cases were computed.

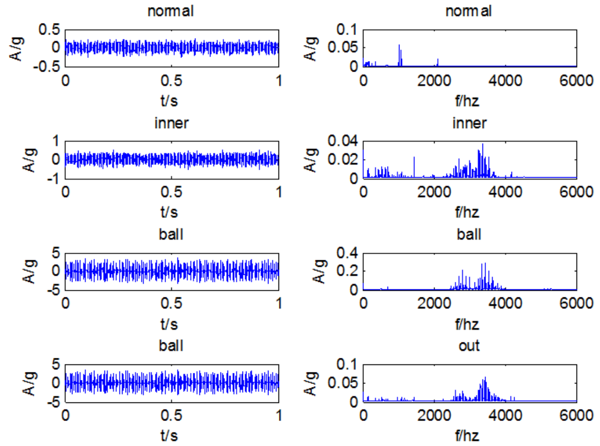

Figure 2. The Original signal waveform and frequency form

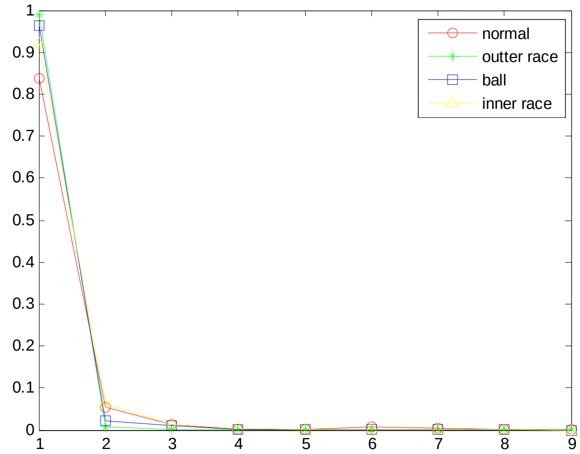

Figure 3. The energy change of each PF

To verify the superiority of the LMD, WPT (wavelet packet transform) and EMD are employed for feature extraction. The WPT and EMD feature vectors are calculated adopting the similar method and are used in the LMD statistical characteristics vectors. The feature vectors extracted from vibration signals by means of WPT, EMD and LMD are employed as the input vectors for Radial Basis Function-Neural Network (RBF-NN) and SVM respectively. During training, the biases and weights are initialized randomly, the learning rate is 1, and the target error is set as 0.05. The three experiments are listed as follow: the first experiment (E1) employed 30 samples for training set, and 10 samples for testing set; the second experiment (E2) employed 20 samples for training set, and 10 samples for testing set; the third experiment (E3) employed 10 samples for training set, and 30 samples for testing set. The testing results are listed in Table 1. Table 1 shows clearly that SVM and RBF-NN classifier with the LMD feature vectors have higher accuracy than the EMD feature vectors and WPT feature vectors. Hence, LMD feature extraction is superior to the others method [12].

Table 1. The average computational results of different algorithm

	LMD-SVM	EMD-SVM	WPT-SVM	LMD-RBFNN	EMD- RBFNN	WPT- RBFNN
E1	100.0	100.0	97.5	92.5	92.5	92.5
E2	100.0	98.75	92.5	88.75	75.00	73.75
E3	98.33	96.66	86.66	80.83	75.00	73.33

Performance Comparison with Different Optimization Algorithm

After the feature extraction by LMD, the sample data sets including are split into training sets and test sets randomly for performance comparison with different optimization algorithm. In this paper, apply the presented method to fault diagnosis of the bearings and compare with GA-SVM and PSO-SVM method. The feature set and the parameters of SVM are optimized simultaneously, and 10 runs were conducted by 10-fold cross-validation to get more reliable results. The compared results show in Table 2. The results in table 2 were obtained by using the proposed IABC-SVM method and traditional GA-SVM and PSO-SVM method. To obtain the optimal parameters C and g, these three methods are directly employed to search parameters in scope of $[10^{-1}\sim10^{3}]$ and $[10^{-1}\sim10^{3}]$. Table 2 shows that the cross-validation rate is 99.96% for the proposed method, 94.91% for the PSO-SVM method and 89.08% for the GA-SVM method, respectfully. The classification accuracy of the IABC-SVM method which reaches 98.77% is obviously higher than the accuracy of the other methods which are respectfully 84.95% and 90.96%.

Table 2. The performance comparison with GA-SVM and PSO-SVM

	C	g	Number of selected feature	Cross-validation rate (%)	Testing accuracy rates	SV number
GA-SVM	237.04	507.98	11	89.08	84.95%	80
PSO-SVM	80.14	19.05	10	94.91	90.96%	86
IABC-SVM	6.32	6.50	18	99.96	98.77%	94

Further, the selected feature subset and original feature are analyzed by means of principal component analysis method to to validate the effect of feature selection of the presented method in this paper. Figure 4 shows the comparison results which can clearly distinguish the four types of condition (normal, ball, inner race and outer race).

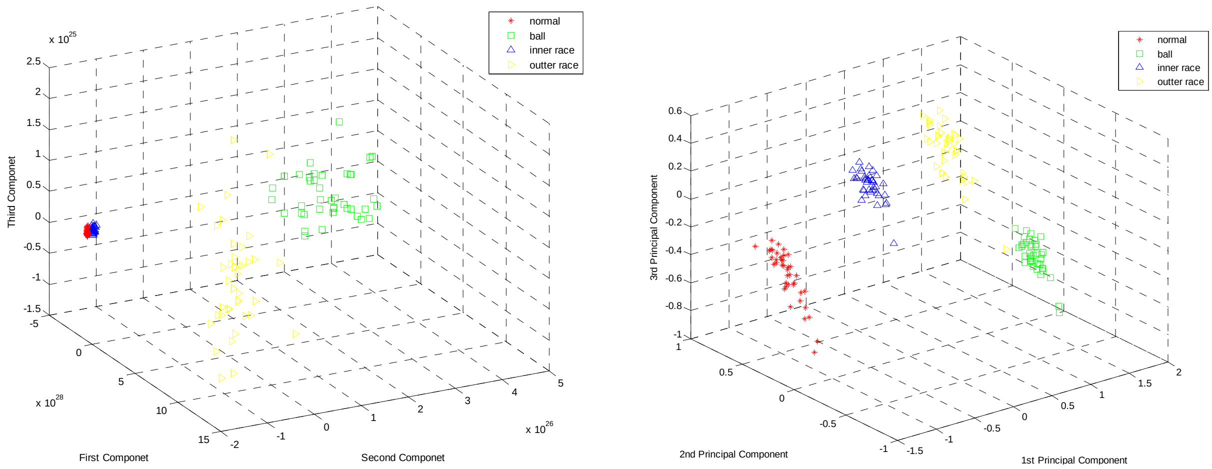

Figure 4. The principal component analysis with all features (left) and selected features (right)

Conclusions

In this paper, an intelligent fault diagnosis model is presented. The LMD method is employed to extract time-domain statistical characteristics, frequency-domain statistical characteristics, and derive rich faulty information from vibration signals of rotating machinery. To improve classification accuracy with the most superior features selected from the original feature set, an intelligent fault diagnosis method based on LMD, SVM and improved artificial swarm (IABC) is presented in this paper and is employed in fault diagnosis of rolling element bearings. The test results show that the proposed method has more accuracy than traditional GA-SVM and PSO-SVM method, because it can adopt the most superior features to detect abnormal work condition in bearings and can identify the category and severity of faults.

Acknowledgements

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