Research Journal of Applied Sciences, Engineering and Technology 6(5): 895-899, 2013
DOI:10.19026/rjaset.6.4138
ISSN: 2040-7459; e-ISSN: 2040-7467

Submitted: October 30, 2012 Accepted: December 15, 2012 Published: June 25, 2013

Research Article

A Novel Fault Diagnosis Method for Rolling Element Bearings Using Kernel Independent Component Analysis and Genetic Algorithm Optimized RBF Network

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Abstract: This study focuses on the defect detection of rolling element bearings using a novel method. In the bearing fault diagnosis, the fault feature extraction is also a key issue for successful fault detection. However, the vibration signals acquired by accelerometers are often mixed with noise signals. These mixtures may influence the fault feature extraction and hence deteriorate the performance of the fault diagnosis. To address this problem, a novel method is presented in this study to enhance the performance of the fault diagnosis of rolling element bearings. In this new method, the Kernel Independent Component Analysis (KICA) was firstly employed to fuse multi-sensor signals to eliminate noise signals. Then a RBF network was used to classify the fault patterns. To improve the fault identification, the Genetic Algorithm (GA) was adopted to optimize the parameters of the RBF network. Experiment tests on a rolling bearing fault diagnosis set-up have been carried out to verify the performance of the proposed method. The test results show that show the KICA can remove the noise effectively and the GA optimized RBF network can provide accurate fault detection results. In addition, the new method has been compared with the single RBF network model and ICA-RBF model. The comparison indicates that the proposed KICA-RBF model outperforms the other two rivals with a fault detection rate of 92.3%.

Keywords: Fault diagnosis, KICA, RBF, rolling element bearings

INTRODUCTION

As a key part in rotating machinery, the rolling element bearings are prone to damage and failure. According to statistics (Li *et al*., 2010), the failures of rotating machinery caused by rolling bearing damages accounted for about 30% of all broken-downs. Therefore, it is essential to detect the rolling bearing faults in time to prevent damages of rotating machinery. Although a large number of research literatures have been done for rolling bearing fault diagnosis (Hasan and Kenneth, 2004; Loparo, 2004; Kankar *et al*., 2011), the noise removal problem is always a hot topic in this research field. To eliminate the noise mixed along the sensors, several methods have been proposed by the scholars. These methods include the Wavelet de-noising (Li *et al*., 2011a), Kalman filter (Li *et al*., 2012d), etc. However, these methods only can analyze one sensor at a time. Although the 2-D Fourier de-noising can analyze two orthogonal signals simultaneously, it cannot handle more than two sensors. In fact, the vibration of the rolling bearings transmits from different directions in the space (Li *et al*., 2012a). Hence, it is reasonable to analyze the bearing vibration using multiply sensors and process the signals at one time. In such a situation, multi-signal fusion problem has become an urgent and practical technology and received worldwide attentions. How to develop and use the multi-sensor signals to detect bearing damage is the hot spot in the research field of fault diagnosis (Li *et al*., 2010, 2012a, b, c).

The inner race crack, outer race crack, cage crack and roller erosion are the most representative rolling bearing fault types. These four defect types cover almost all known rolling bearing faults. The serious challenge on these four fault types is that the contamination of noise in the bearing vibration data. Usually, there are several sources mixed into the bearing vibration data that one need to separate them out before the fault diagnosis. To overcoming this problem, some useful noise removal methodologies have been presented in the literatures. Li *et al*. (2011a) used the Wavelet de-noising approach to remove the noise components in the vibration of a gearbox. Experiment tests have shown effective performance of the noise elimination on the fault diagnosis of gearboxes. Li *et al*. (2012d) used the Kalman filter to eliminate the noise components in the vibration of rolling bearings. They carried out the experiment tests and the test results showed that the Kalman filter can effectively remove the noise signals and hence enhance the fault diagnosis of rolling bearings. In addition, since the full spectrum (Lee and Han, 1998; Goldman and Muszynska, 1999) is capable of processing a two-

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dimensional signal measured from two orthogonal sensors, it has been adopted to integrate information from two sensors. However, these methods only can handle less than two sensors. For a higher number of sensors, novel approaches should be exploited. This is because the transmission of vibration is not limited in a direction and location, but distributes in every direction. Fortunately, the Independent Component Analysis (ICA) is a competent technology for the separation of different sources and has powerful ability in fusion of multiply sensors, i.e., more than two sensors (Li *et al*., 2012a, b). Hence, the application of ICA has been found in the field of fault diagnosis. However, the popular Fast ICA algorithm (Li *et al*., 2012a, b) is not effective for the nonlinear case such as the case of rolling bearing. This is because in practice the bearing vibration is the nonlinear mixture of several sources. Some study has been done using the linear ICA algorithms to solve the fault diagnosis in mechanical systems, but little study has addressed the nonlinear ICA problem on the fault diagnosis of rolling bearings. Since the Kernel ICA (KICA) (Bach and Jordan, 2002) can overcome the shortcomings of nonlinear ICA to deal with the nonlinear BSS problems, it is very urgent to test the performance of KICA in the fault diagnosis of rolling bearings.

In order to handle the nonlinear BSS problem to eliminate noise signals in the fault diagnosis of rolling bearings, a novel method based on the integration of KICA and artificial neural network has been proposed in this study. The KICA was firstly used to fuse multiply sensors to extract inherit bearing vibration signal with noise removed. Then the RBF network was employed to identify the fault types. In order to enhance the detection rate of the RBF network, the GA was adopted to optimize the parameters of the network. To verify the new method, experiments have been carried out in a rolling bearing test bed. The analysis results show that the noise can be eliminate efficiently by the KICA and the fault diagnosis rate is up to 92.3%. Hence, the proposed method is useful for the fault diagnosis of rolling bearings.

THE PROPOSED DIAGNOSIS METHOD

Since the bearing vibration signal is corrupted by noise thoroughly, which is often unable to be described by analytical equations, the KICA (Bach and Jordan, 2002) is employed to remove the noise. The concept of the kernel trick allows ICA to be able to solve nonlinear BSS problems, which is very suitable for the case of rolling bearing fault detections. In this study the KICA and RBF network are employed for the rolling bearing fault detection. Moreover, to improve the generalization of the RBF network, the GA algorithm is adopted to optimize the RBF parameters. The theories about the proposed method are briefly described below.

The Kernel Independent Component Analysis (KICA): Assuming *p* unknown independent sources **s** = $[s_1\ s_2\ \dots\ s_p]^T \in R^p$, the measured signals $x = [x_1\ x_2\ \dots\ x_q]^T \in R^q$ ($p \le q$) are linear combination of s, i.e.:

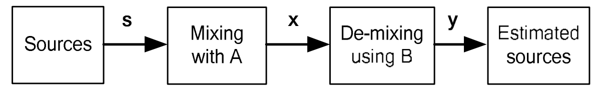

Fig. 1: The principle of the BSS

$$x = A.s \tag{1}$$

where, $A \in R^{q\times p}$ is the mixing matrix. The principle of the ICA and its BSS process is shown in Fig. 1.

The aim of ICA is to find a transformation matrix $B \in R^{p\times q}$ to make $y = B \bullet x \approx s$. Linear ICA is unable to deal with nonlinear BSS. To overcome this problem, Bach and Jordan (2002) proposed the KICA to maximize independence of nonlinear mixtures using the kernel correlation minimized. For details of KICA, one can refer to Bach and Jordan (2002).

The GA optimized RBF network: In general, there exists a certain relationship between the fault features and fault types. A neural network classifier can find this connection. Since the RBF network has better nonlinear mapping capability than BP network (Li *et al*., 2011b), this study used the RBF network to establish rolling bearing fault detection model. However, the efficiency of the neural network relies on its structure. It is very important to determine improper structure of the neural network. The traditional way obviously can't satisfy the need of network high-dimensional data which relies on expert experience to set network structure parameters. Therefore, this study adopts Genetic Algorithm (GA) to optimize the parameters of the RBF network to lighten the impact of network parameters on the detection rate.

The parameters of a RBF network are the hidden node number, width and centre value of the base function. In order to obtain optimal network structure parameters, the GA was employed to optimize the above mentioned parameters. The GA has three main operators, including selection, crossover and mutation. The goal of these operations is to pick out best values of these parameters from generation to generation in the iteration. The processes of the GA optimization can be expressed as follows:

1. Code the hidden node number, width and centre into GA chromosomes by binary coding to form a GA individual. Several individuals form a population space
2. Initialize the individuals
3. Calculate the fitness values of the individuals
4. Do crossover and mutation to generate new individuals in new population space
5. Decode the new population space to calculate the Fitness values of the new individuals

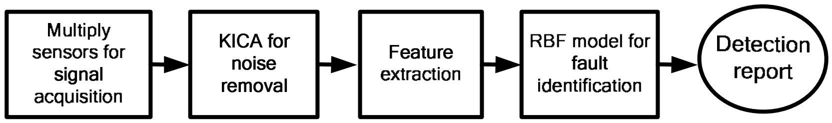

Fig. 2: The diagram block of the fault diagnosis of rolling bearings

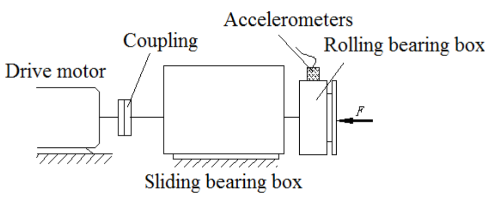

Fig. 3: The rolling bearing experimental tester

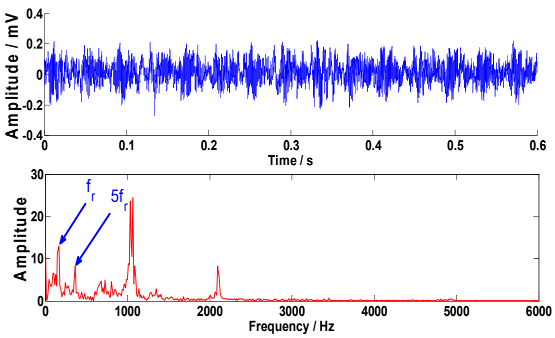

Fig. 4: The time and frequency spectra of roller erosion

6. If the results can satisfy the termination conditions, then stop the optimization process. Otherwise, return step (4) for iteration

The workflow of the fault diagnosis: The workflow of the fault diagnosis in this study is given as follows:

- Record the vibration signals of the rolling bearing using multiply sensors.
- Do the BSS on the sensor signals using KICA to fuse the multi-signal into one useful signal.
- Extract the features of the separated signal. These features include the Root Mean Square (RMS), mean frequency, skewness and kurtosis.
- Train the RBF network using the features to get a fault detection model. Optimize the RBF model using GA.
- Test the performance of the RBF model

A diagram block of the workflow is illustrated in Fig. 2.

EXPERIMENT TESTS AND RESULTS

In order to evaluate and validate the performance of the proposed fault diagnosis method for rolling bearings, experiment tests have been implemented in a
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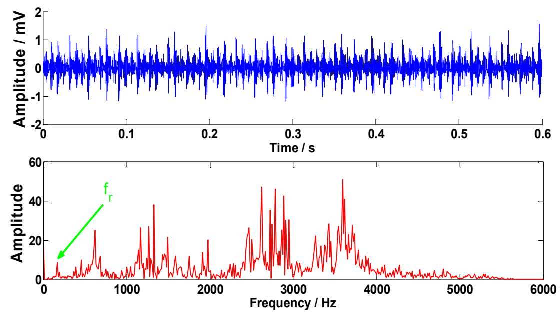

Fig. 5: The time and frequency spectra of inner race crack

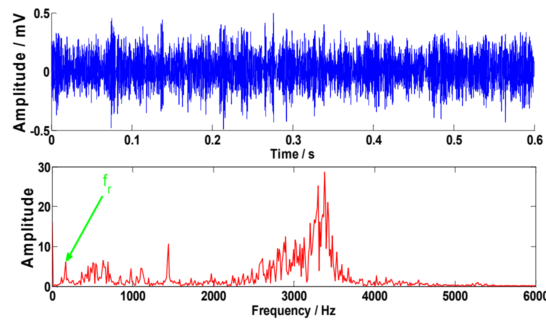

Fig. 6: The time and frequency spectra of outer race crack

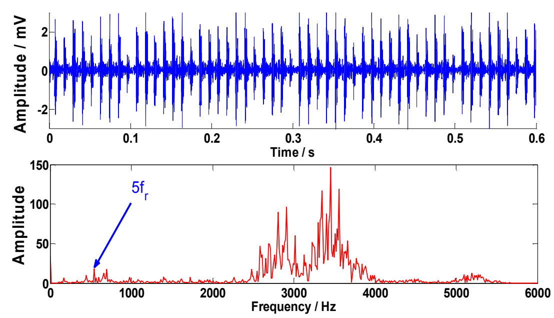

Fig. 7: The time and frequency spectra of cage crack

rolling bearing set-up. Figure 3 shows the experiment device. The experiment test platform mainly consists of a 1 kW induction motor driver, a flexible coupling, a sliding bearing box, a rolling bearing box with SKF 6205 rolling element bearing and 4 accelerometers. The accelerometers are mounted on the surface of rolling bearing box at four different directions. Hence, the accelerometers can collect the bearing vibration data from four directions.

In order to simulate the rolling bearing faults, we have prepared four fault types, i.e., inner race crack, outer race crack, cage crack and roller erosion. For

Table 1: The fault detection results

	Training		Testing	
Detection model	Detection rate (%)	Uncertainty (%)	Detection rate (%)	Uncertainty (%)
GA-RBF	81.3	9.3	80.0	9.7
ICA plus GA-RBF	85.7	6.7	84.3	6.7
KICA plus GA-RBF	92.3	3.3	92.3	3.7

Table 2: Optimization performance of GA to the RBF model

KICA-GA-RBF		KICA-RBF	
Detection rate	Uncertainty	Detection rate	Uncertainty
92.3	3.7	90.7	4.7

every fault type, the rolling bearing has been tested for 10 h. The accelerometers sample the vibration signals every 10 min. The sample frequency is 10 kHz.

Figure 4 to 7 shows the time and frequency spectra of the tested rolling bearings after the KICA processing. It can be seen from the figures that the KICA can keep the characteristics of the bearing vibration with the noise depressed. The spectra vary with the change of the bearing working conditions. As a result, useful features of the bearing vibration signals can be extracted. In this study, we have calculated the RMS, mean frequency, skewness and kurtosis of the vibration signals. These features will be input into the RBF model for the fault type recognition.

We have collected 60 samples for each fault in the experiments. Half of the samples are used to train the RBF network and the rest are applied to testing the trained RBF model. The GA is employed in the training of the RBF network. Table 1 shows the fault detection results. In the experiments, we have compared the performance of the RBF model, ICA-RBF model and KICA-RBF model. We also compared the GA optimization. Table 2 shows the optimization performance.

It can be seen from Table 1 that the performance of the proposed method is the best one among the three models. Owing to the nonlinear BSS processing, the inherit characteristics of the nonlinear signals of the rolling bearings can separated by the KICA. However, since the linear ICA is unable to deal with the nonlinear case, the fusion performance of the multiply sensors is not good as the KICA. As a result, the diagnosis rate of the ICA based model is less than the KICA based RBF model. Nevertheless, according to the diagnosis results, the BSS processing can enhance the fault detection performance. By comparing the BSS based model to the single RBF model, it can be seen that the detection rate has been increased by 4.4% or better while the uncertainty rate has been raised by 2.6%. This indicates great improvement of the fault detection performance.

In Table 2, it can be seen that after the GA optimization, the detection rate has been increased by 1.6% and the uncertainty rate has been raised by 1.0%. As a result, the GA can help the RBF find proper parameters and hence eliminate the influence of these variables on the detection result. Therefore, the proposed method shows promising performance on the fault diagnosis of rolling element bearings.

CONCLUSION

Since the measured vibration signals can be considered as mixtures of bearing vibration and disturbance noise, it is essential to adopt information fusion technology to make full use of multiply sensors. Useful diagnostic information can be extracted under the guidance of the information fusion. The fault detection and diagnosis then can be achieved reliably using artificial neural networks. To address the mentioned issue, a new fault diagnosis method based on the integration of KICA and GA-RBF network is proposed in this study. The innovation of this study is that it adopts the nonlinear BSS and evolutionary algorithm to improve the fault detection ability of the RBF network. A series of experiments have been carried out to verify the proposed method. The analysis results demonstrate that the new method can detect the bearing faults precisely. Future study will use this new method in practice.

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