Fault Diagnosis for a Rolling Bearing Used in a Reciprocating Machine by Adaptive Filtering Technique and Fuzzy Neural Network

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Abstract: - This paper presents a method of fault diagnosis for a rolling bearing used in a reciprocating machine by the adaptive filtering technique and a fuzzy neural network. The adaptive filtering is used for noise cancelling and feature extraction from vibration signal measured for the diagnosis. A fuzzy neural network is used to automatically distinguish the fault types of a bearing by time domain features. Using the signals processed by adaptive filtering, the neural network can quickly converge when learning, and can quickly distinguish fault types when diagnosing. The spectrum analysis of an enveloped time signal is also used for the fault diagnosis. Practical examples of diagnosis for a rice husking machine are shown in order to verify the efficiency of the method. All diagnosis results of the spectrum analysis and the fuzzy neural network show that the method proposed in this paper is very effective even for cancelling highly correlated noise, and for automatically discriminating the fault types with a high accuracy.

Key-Words: - fault diagnosis, adaptive filtering, fuzzy neural network, rolling bearing, Reciprocating Machine, signal processing

1 Introduction

A rolling bearing is an important part that is most often used in rotating machinery. The failure of a rolling bearing may cause breakdown of a rotating machine, and furthermore, a serious trouble also may occur due to the failure. Therefore, the fault diagnosis of rolling bearing is very important for guaranteeing the production efficiency and the plant safety. Up to now, there are many technical papers and reports for fault detection of rolling bearing, but the study subject of these papers and reports are the rolling bearing used in general rotating machinery with steady rotating speed [1]-[7].

The condition diagnosis using vibration method for reciprocating machinery, such as gas engine, vibration selector etc., is more difficult than general rotating machinery with steady rotating speed such electric motor, fan etc., because the vibration level is higher and shocking even if it is in the normal state. Sudden breakdown of reciprocating machinery may occur due to the difficulty of fault detection in a part of reciprocating machinery.

In order to diagnose fault of a rolling bearing used in a reciprocating machine, this paper proposes a diagnosis method using adaptive signal processing and fuzzy neural network for raising the accuracy of the fault diagnosis.

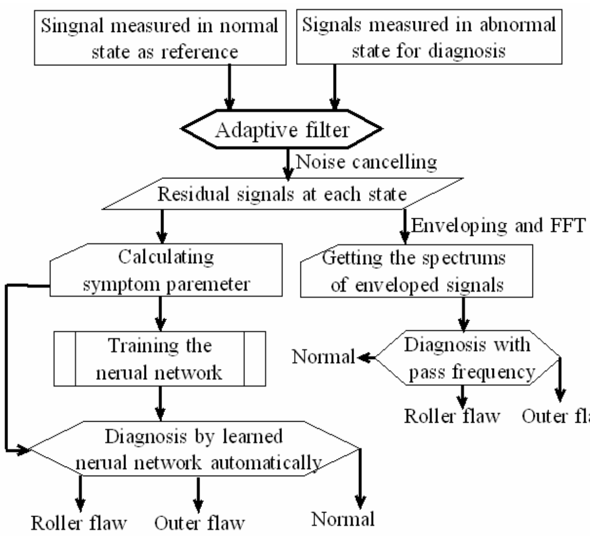


Fig.1 A flowchart of fault diagnosis

The outlined flowchart of the method is shown in Fig. 1. The signal measured in normal state is used as the reference signal of the adaptive filter. The inspection signal for fault diagnosis is measured at the same position, and the operating condition is the same as that of the reference signal. When inputting the reference signal and the inspection signal into the adaptive filter, the adaptive filter will output the residual signal, and the residual signal will be used to the fault diagnosis of a rolling bearing by the spectrum analysis of enveloped time signals and fuzzy neural network.

2 Adaptive Filtering Technique

2.1 Adaptive Filtering and LMS Algorithm

Adaptive filters have been applied in signal processing and control, as well as in many practical problems [8]. Adaptive filtering or adaptive estimation is a digital signal processing (DSP) algorithm that is self-adjusting based on input data, and which can improve estimation or detection performance in systems' problems. As the signal continues into the filter, the adaptive filter coefficients adjust themselves to achieve the desired results, such as identifying an unknown filter or cancelling noise in the input signal. Many adaptive filtering algorithms are iterative methods for solving error minimization problems. The most commonly used adaptive systems are those based on the Least Mean Square (LMS) adaptive algorithm.

The LMS algorithm is simple, robust and most popular algorithm for adaptive filtering applications [8]-[11]. Its simplicity and low computational complexity makes this algorithm an attractive solution for many practical problems [12]. The adaptive filter adjusts its coefficients to minimize the mean-square error between its output and that with the unknown system [13]. The LMS algorithm is a practical scheme for realizing Wiener filters; it adapts the filter tap weights minimizing the mean square error.Please, leave two blank lines between successive sections as here.

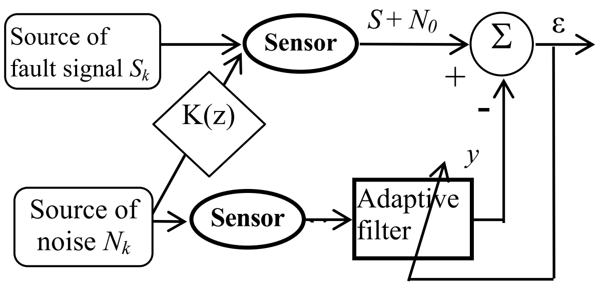


Fig.2 A adaptive noise cancelling

2.2 Adaptive Noise Cancelling

A signal S_0 corrupted with noise N_0 is received at the primary sensor while the bearing is operated under faulty conditions as shown in Fig.2.

The signal S is the fault signal from the bearing and N_0 is the noise of the vibration signal measured from normal bearing. A reference noise N_1, which is related to noise N_0 in some unknown way but not correlated with signal S, is received by the reference sensor in normal state. The output filter y is then adaptively filtered to match N_0 as close as possible. Then the filter output is then subtracted from the primary input $S+N_0$ to produce the system output ε called residual signal such that:

$$\varepsilon = S + N_0 - y \tag{1}$$

Then

$$\varepsilon^2 = S^2 + (N_0 - y)^2 + 2S(N_0 - y) \tag{2}$$

Taking the equation of both sides of (2)

$$E(\varepsilon^2) = E(S^2) + E\left((N_0 - y)^2\right) \tag{3}$$

The adaptive filter output is

$$y = \mathrm{W}^{\mathrm{T}}\mathrm{X} \tag{4}$$

$$E(\varepsilon^2) = E(S^2) + E\left((N_0 - \mathrm{W}^{\mathrm{T}}\mathrm{X})^2\right) \tag{5}$$

where W is the weight vector and X is the input vector. The signal power $E(S^2)$ will be unaffected as the filter weights are adjusted to minimize $E(\varepsilon^2)$:

$$\min E(\varepsilon^2) = E(S^2) + \min\left((N_0 - \mathrm{W}^{\mathrm{T}}\mathrm{X})^2\right) \tag{6}$$

For an optional filter weights, the output y is the best least square estimate of primary noise N_0 From the following equation:

$$(\varepsilon - S) = (N_0 - y) \tag{7}$$

The adjustment of the filter weights to minimize the output power causes ε to be the best least square estimate of the signal S.

The adaptive noise cancelling filtering is easily implemented by computer software. It is the same as the least mean square (LMS) algorithm. This algorithm is shown in the following equation [11]:

$$\mathrm{W}_{j+1} = W_j + 2\lambda\varepsilon_j\mathrm{X}_j \tag{8}$$

where W_j is the weight vector at the jth instant of time, X_j is the reference input vector at the jth instant of time, ε_j is the error signal at the jth instance of the output of the noise canceller, and λ is the gain constant that regulates the speed and stability of the adaptation. To insure the convergence of the adaptive algorithm, the value of λ should be chosen [14] such that

$$0 < \lambda < \frac{1}{(L+1)(signalpower)} \tag{9}$$

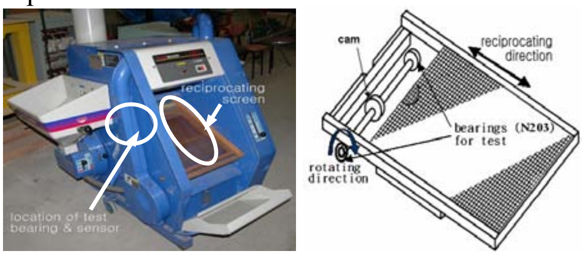
where L is the index of the last filter weight. The calibration of the respective parameters, such as λ

parameter is automatically determined by the soft ware attached in the reference[9].

3 Experiment System for Diagnosis

3.1 The Reciprocating Machine

A rice husking machine with 750W electric motor was utilized for the test of bearing diagnosis as shown in Fig.3. This machine is used for post harvest operation wherein the rice seed is husked prior to milling. Rice husking involves the removal of husk from the rough rice. During husking, the grain is subjected to shear or impact force. The grain husked by the impeller and drop on the reciprocating screen. The grain and impurities then be segregated through the reciprocating motion of the screen created by the eccentric bearing. The power is transmitted by a v-belt connected on other mechanism to drive the pulley in producing reciprocation.



(a) A rice husking machine, (b) A reciprocating screen

(c) Sensors 1 & 2 (d) Sensor 3

Fig.3 The reciprocating machine for diagnosis

(a) Outer race flaw (b) Roller race flaw

Fig.4 The bearing flaws

The fault bearing is installed at the main shaft one at a time. Three acceleration sensors are placed to measure vibration signal. The sensor 1 and 2 shown in Fig.3 (c) are used to detect the fault of the bearing for diagnosis, and fixed at the bearing casing in vertical and horizontal direction respectively. The sensor 3 shown in Fig.3 (d) is placed at the opposite side and located near the pulley that drives the main shaft in vertical direction.

The vibration signals are measured at a constant rotating speed of 496rpm for the adaptive noise cancelling. The sampling frequency for the measurement is 200 kHz, and the sampling time is 20s.

3.2 Rolling Bearing for Diagnosis

In this work, the simulated flaw (abnormal state) is located at the roller and outer race of the rolling bearing for the tests of the condition diagnosis.

NTN N203 bearing (the bearing pitch diameter is 28mm, the roller diameter is 5mm, the contact angle is 0 degree, and the number of rollers is 10.) is utilized in this machine. Fig.4 illustrates the simulated flaws on roller and outer race. These faults were artificially localized in a rectangular shape at the roller and outer race by a special machining technique to induce a crack or flaws. The width and depth of the flaws are 0.4mm.

4 Diagnosis and Discussion

4.1 Noise Cancelling by Adaptive Filtering

The signals detected in abnormal states are as the test signals to be diagnosed, and the signal detected in normal state at the same detecting position and same operating condition is as the reference signal that can be obtained easily in general.

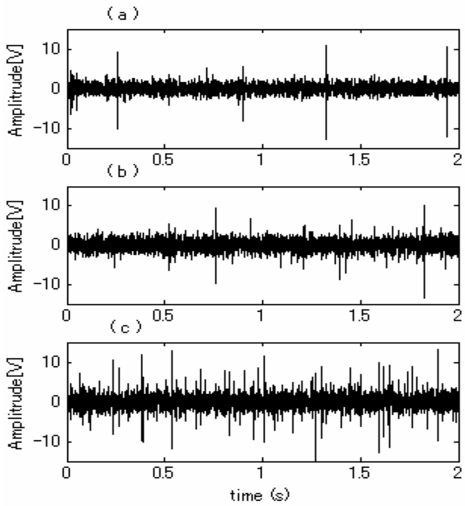


Fig.5 Original bearing vibration signals: (a) Normal signal, (b) Outer race flaw signal, (c) Roller race flaw signal

Fig.5 shows the raw signal measured in three different bearing states. Obviously, as shown in Fig.5 (a), there are random impulses in the vibration signal of normal state because of the reciprocating mechanism. The effect of noise in the signal measured for the diagnosis is stronger than the fault signal from bearing flaw, and the fault symptom in time domain is not evident (specially, Fig.5 (b)), but the magnitude level of the signal of roller race flaw, as shown in Fig.5(c), is higher than that of the outer race flaw shown in Fig.5 (b).

The adaptive noise cancelling method has been applied to the extraction of the fault signals of the bearing. Fig. 6 shows the extracted fault signals of bearing flaws. The pulse signals caused by bearing flaws in the extracted fault signals shown in Fig. 6 are more remarkable than those in the signals before noise cancelling.

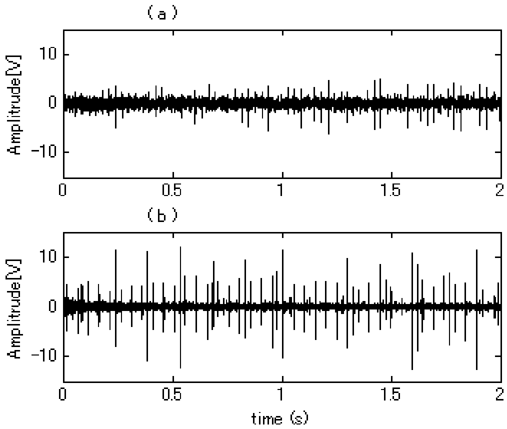


Fig.6 Bearing signals after adaptive noise cancelling: (a) Outer race flaw signal, (b) Roller race flaw signal

4.2 The Enveloped Spectrum Analysis

To distinguish each fault state of a bearing, pass-frequency values of roller race flaw (f_R) and outer race flaw (f_O) can be calculated by following equations;

Roller race flaw: $$f_R = \frac{Df_r}{d}\left(1 - \frac{d^2}{D^2}\cos\alpha\right) \quad (10)$$

Outer race flaw: $$f_o = \frac{zfr}{2}\left(1 - \frac{d}{D}\cos\alpha\right) \quad (11)$$

where z : the number of rolling elements;

f_r : the rotating frequency;

d : the diameter of rolling elements;

D : the pitch diameter;

α : the contact angle of rolling element

In the case of the study, f_R and f_o is 44.8 Hz and 34 Hz respectively.

Fig. 7 shows the enveloped signal spectrums of outer race flaw with high-pass filtering (cut-off frequency is 3 kHz) and adaptive filtering respectively. The spectrum of enveloped signal with adaptive filtering (Fig.7 (b)) clearly shows the peak at the pass frequency of the outer race flaw and exhibits many harmonics that correspond to the pass frequency. These peaks (Fig.7 (b)) after adaptive filtering application are more noticeable than those with high-pass filtering (Fig.7a). It is clearly evident that the bearing flaws can be detected and distinguished more easily after adaptive filtering. The roller flaw spectrum of enveloped signal after adaptive filtering (Fig.8 (b)) is also obviously higher than that with high-pass filtering (Fig.8 (a)). By these results of the diagnosis test, the method proposed in this paper is efficient for condition diagnosis of rolling bearing used in the reciprocating machine.

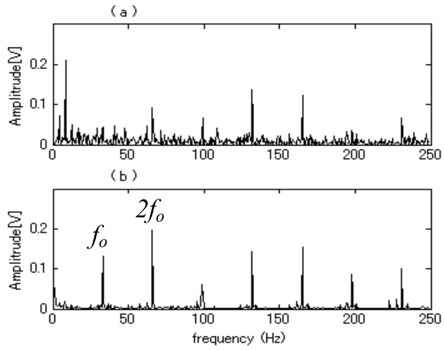


Fig.7 Bearing enveloped signal spectrum of outer race flaw (a) With high-pass filtered signal, (b) With adaptive filtered signal.

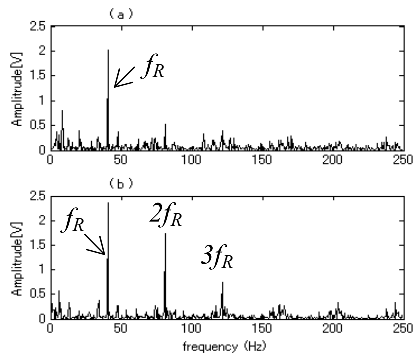


Fig.8 Bearing enveloped signal spectrum of roller race flaw (a) With high-pass filtering, (b) With adaptive filtering.

4.3 Diagnosis by the Fuzzy Neural Network

4.3.1 The symptom parameters

For automatic diagnosis, the symptom parameters are needed that can sensitively distinguish fault types. Here, three of these parameters, commonly used for the fault diagnosis of plant machinery, are considered for the fuzzy neural network [15]. Let x_i (i=1~N) be the discrete data of a normalized signal. Those symptom parameters in the time domain are described as follows.

$$p_1 = \frac{\sum_{i=1}^{N}(x_i - \bar{x})^4}{N\sigma^4} \quad (12)$$

$$p_2 = \frac{\bar{x}_p}{\bar{x}_{abs}} \quad (13)$$

$$p_3 = \frac{\sigma_p}{\bar{x}_p} \quad (14)$$

where σ and $\bar{x}$ are the standard deviation and the mean value of x_i respectively.

$$\bar{x}_{abs} = \frac{\sum_{i=1}^{N} |x_i|}{N} \quad (15)$$

$\bar{x}_p$ is the average of peak values of $|x_i|$ and σ_p is the standard deviation of peak values of x_i.

Here, we divided the processed signal of each state into 20 signal parts, and the sample number of per signal part is 61440 (the sampling time is 0.3s (about 2.5 shaft rotations)). Each of these parts is used to calculate the symptom parameters as the training data for the fuzzy neural network.

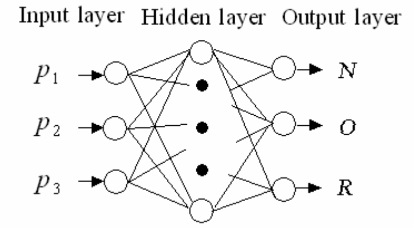


Fig.9 The fuzzy neural network

4.3.2 The fuzzy neural network

In this work, the fuzzy neural network called the partially-linearized neural network (PNN) is trained and implemented for fault diagnosis [15]. As shown in Fig.9, the PNN consists of the input layer, one hidden layer and the output layer. The inputs to the neurons in the first layer are the sets of the symptom parameters at each state. The number of neurons in the hidden layer is eighty. The outputs in the last layer are N, O and R, which are the possibility grades of normal state, outer flaw state and roller flaw state, respectively. In the training stage, the teacher values outputted from the first neuron in the last layer are set as 1 and 0 for normal state and abnormal states respectively. Similarly, the teacher values outputted from the second neuron in the last layer are set as 1 and 0 for the roller flaw state and other states respectively. The teacher values outputted from the third neuron in the last layer are set as 1 and 0 for the outer race flaw state and other states respectively.

4.3.3 Diagnosis and Discussion

We calculate values of the symptom parameters using the signals with high-pass filtering (cut-off frequency is 3 kHz) and adaptive filtering for training the fuzzy neural network, respectively.

Using the symptom parameters calculated from the high-pass filtered signals, the fuzzy neural network cannot converge. It can be explained that the symptom parameters calculated form the high-pass filtered signals are poor, and cannot discriminate the fault types. As an example, the distributions of a parameter in each state are shown in Fig.10, where, N, O, and R is the distribution of the parameter at the normal state, the outer flaw state, and the roller flaw state, respectively.

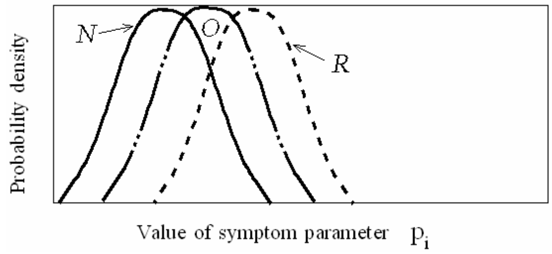


Fig.10 The distributions of the parameter with the high-pass filtered signals

However, using the symptom parameters calculated with adaptive filtered signals, the neural network can get a good convergence. As an example, the distributions of the parameter in each state are shown in Fig.11. It can be seen from Fig.11, the values of the symptom parameters are sensitive change with machinery states, by which the fault types can be distinguished.

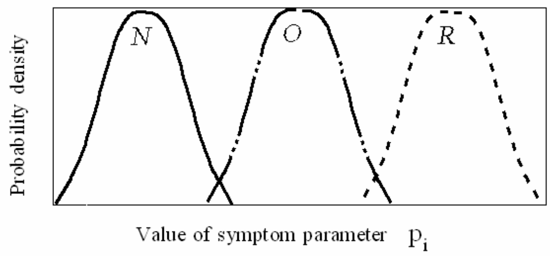


Fig.11 The distributions of the parameter with the adaptive filtered signals

The PNN was quickly convergent by learning the training data calculated with the adaptive filtered signals. Parts of diagnosis knowledge of the PNN are shown in Table 1. In order to verify the diagnostic capability of the PNN, we used the data measured in each state which had not been learnt by the PNN. When inputting the test data, the learnt PNN can correctly and quickly diagnose those faults with the possibility grades. Table 2 shows the diagnosis results for each state. According to the test results, the probability grades output by the PNN show the correct judgment in each state. Therefore, the PNN using the signals processed by adaptive filter can precisely distinguish the type of bearing fault.

Table 1 Parts of diagnosis knowledge

p_1	p_2	p_3	N	O	R
0.81	1.20	0.73	1	0	0
1.15	8.91	1.20	0	1	0
2.34	14.3	2.49	0	0	1
…	…	…	…	…	…

Table 2 Diagnosis results

p_1	p_2	p_3	N	O	R	Judge
0.83	1.74	0.75	0.99	0.01	0.00	***N***
1.06	8.18	1.07	0.01	0.99	0.00	***O***
2.13	16.7	2.26	0.01	0.02	0.97	***R***

5. Conclusion

The fault diagnosis of a rolling bearing used in a reciprocating machine is more difficult than that used in general rotating machine since the vibration signals measured at any point of the machine often contain stronger noise than fault signal. Therefore, it is important to remove the noise from the measured signal as much as possible for accurately identifying fault types. This paper proposed a diagnosis method for a rolling bearing using a adaptive signal processing and a fuzzy neural network. The adaptive filtering is used for noise cancelling and feature extraction from vibration signals measured for the diagnosis. The fuzzy neural network is used to distinguish the fault types with time domain features. A real farm machine called "a rice husking machine" as an example is used for verification of this method.

The results of the enveloped spectrum analysis show the adaptive filtering by LMS algorithm is very effective. Using those parameters calculated with adaptive filtered signals, the fuzzy neural network can quickly converge when learning, and can automatically distinguish fault types with a high accuracy when diagnosing. The diagnosis results by the fuzzy neural network also show the efficiency of the method proposed in this paper.

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