

# RECENT RESEARCH RESULTS ON INTELLIGENT METHODS FOR CONDITION DIAGNOSIS OF ROTATING MACHINERY

Huaqing WANG<sup>1,2</sup> and Peng CHEN<sup>1\*</sup>

<sup>1</sup> Graduate School of Bioresources, Mie University, Tsu, Mie, 514-8507, Japan

<sup>2</sup> School of Mech. & Elec. Eng., Beijing University of Chemical Technology, Beijing, 100029, China

\*corresponding author: Peng CHEN, email: chen@bio.mie-u.ac.jp

Huaqing WANG, email: wanghq\_buct@hotmail.com

## Abstract

This paper reports several intelligent diagnostic approaches for rotating machinery based on artificial intelligence methods and feature extraction of vibration signals. That is: the diagnosis method based on wavelet transform, rough sets and neural network; the diagnosis method based on sequential fuzzy inference; diagnosis approach by possibility theory and certainty factor model; the diagnosis method on the basis of adaptive filtering technique; feature extraction method based on information theory; the diagnosis method by time-frequency techniques and the relative crossing information (RCI) in unsteady operating conditions. These methods had been successfully applied to condition diagnosis in different kinds of practical rotating machinery.

**Keyword:** Condition diagnosis, Intelligent Method, Rotating Machinery, Feature extraction, Vibration signal.

## 1 Introduction

In the case of condition diagnosis of the plant machinery, particularly rotating machinery, the utilization of vibration signals is effective in the detection of faults and the discrimination of fault type, because the signals carry dynamic information about the machine state. Condition diagnosis depends largely on the feature analysis of vibration signals, so it is important that the feature of the signal can be sensitively extracted at the state change of a machine [1-4]. However, feature extraction for fault diagnosis is difficult because the vibration signals measured at any point of the machine often contain a strong noise. Furthermore, diagnostic knowledge is ambiguous because definite relationships between symptoms and fault types cannot be easily identified. In addition, due to the complexity of plant machinery conditions, and the number of fault states to be identified is enormous, it is very hard to find one or several symptom parameters that can identify all of those faults perfectly, simultaneously. Particularly, it is difficult to judge the relationship between fault states and the symptom parameters by a theoretical approach [5-7].

For the above reasons, in order to remove the noise from the measured signal, extract the signal feature and explain the relationship between symptom parameters and machinery conditions, and improve the efficiency

and accuracy of fault diagnosis at an early stage, we have proposed several intelligent diagnosis methods for rotating machinery based on artificial intelligence methods and feature extraction of vibration signals.

## 2 Diagnosis method based on wavelet transform, rough sets and neural network

An intelligent diagnosis method for rotating machinery is proposed using the wavelet transform (WT), the rough sets (RS) and the fuzzy neural network (NN), on the basis of the features of vibration signals [7-8]. The flowchart of this approach is shown in Fig.1.

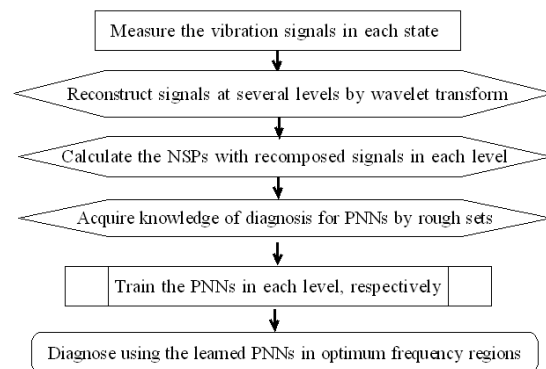


Fig. 1 Flowchart of intelligent diagnosis method

### 2.1 Feature extraction by WT

The WT is a time-frequency signal analysis method, which has also been used for feature extraction and noise canceling of measured signals [1-2]. Here, WT performed to extract fault features of each state from measured signals to capture the true fault information across optimum frequency regions. The signals can be decompose into some levels in approximations and details by wavelet function. After use of the wavelet reconstruction function, the signal constituents at each level of the decomposition are reconstructed.

### 2.2 Definition of symptom parameters

For automatic diagnosis, symptom parameters (SPs) are needed that can sensitively distinguish the fault types. A large set of SPs has been defined in the pattern recognition field [6-8]. In the present work, nondimensional symptom parameters (NSPs) in time domain are considered, and are calculated with the reconstructed time signals of each level in each state to be diagnosed, respectively [7].

## 2.3 Fuzzy neural network

Although many studies have been carried out to investigate the use of NNs for automatic diagnosis of machinery condition, most of these methods have been proposed to deal with discrimination of fault types collectively [9-13]. However, the conventional NN cannot adequately reflect the possibility of ambiguous diagnosis problems, and will never converge when the first-layer parameters have the same values in different states [14].

To solve this ambiguous problem, the fuzzy neural network is realized with the developed back propagation NN called as “the partially-linearized neural network (PNN)”. The principle of the PNN for the fault diagnosis had been described in [7].

## 2.3 Knowledge acquisition by rough sets

Rough sets theory [15], a mathematical tool to deal with vagueness and uncertainty, has found many interesting applications. In this case, to diagnose states accurately, decrease the number of input parameters for the NN, and improve the efficiency of NN learning, the rough sets are used to acquire diagnosis knowledge.

## 2.4 Verification

Practical examples of condition diagnosis for a centrifugal pump system are provided to verify the method’s efficiency. Faults which often occur in pump systems, such as cavitation, impeller damage, impeller unbalance and shaft misalignment between the motor and the pump are considered. Original vibration signals measured in each state are decomposed into several levels in low frequency and high frequency by the rbio2.8 wavelet function. After use of the wavelet reconstruction function, the signal constituents at each level of the decomposition are reconstructed in time domain respectively. As input data of PNNs, SPs are calculated with the reconstructed signals.

The PNNs are quickly convergent by learning the training data. We used the data that had not been learned by the PNNs to verify the diagnostic capability of the PNNs. When inputting the test data, the learned PNNs can quickly diagnose those faults with the possibility grades of relevant state.

As examples, Fig. 2 shows a part of diagnostic results. It can be seen from Fig. 2, the detection rates are different for different levels. The features in the different states have appeared in different frequency levels, so we used the recomposed signals and obtained a maximum detection rate in optimum frequency regions for distinguishing relevant state from other states.

According the verification results, the efficiency of NN learning can be also improved by using knowledge acquired by the rough sets. Having the diagnosis knowledge acquired by the rough sets, the PNN can obtain a good convergence when learning. When diagnosing, the PNN is always convergent, and can quickly and automatically distinguish fault types with

high accuracy in optimum frequency regions.

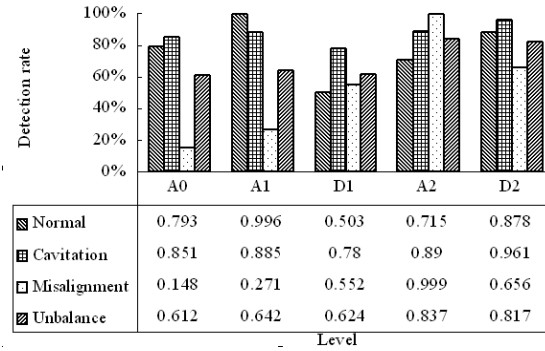


Fig. 2 Parts of detection rates in each state

## 3 Diagnosis method based on sequential fuzzy inference

### 3.1 Basic conception of sequential inference

In the case of fault diagnosis, if we can find several SPs by which most of faults can be diagnosed, conditions of machinery should be easily identified. However, the number of fault states to be identified is enormous, and it is very hard to find one SP or several SPs that can identify all of those faults, simultaneously. Sometimes, an ideal SP with high detection rate does not exist. The SP to identify only two states is quite easy to find [16]. Therefore, a sequential diagnosis inference is proposed. At this time, it is just required to diagnose two states in the various diagnosis steps.

A practical example of a bearing diagnosis by sequential diagnosis is shown in Fig.3. We must distinguish among four states, namely, the normal state, outer race flaw state, inner race flaw state, and roller element flaw state, sequentially. In those diagnostic stages, we should distinguish only two states in one diagnostic step.

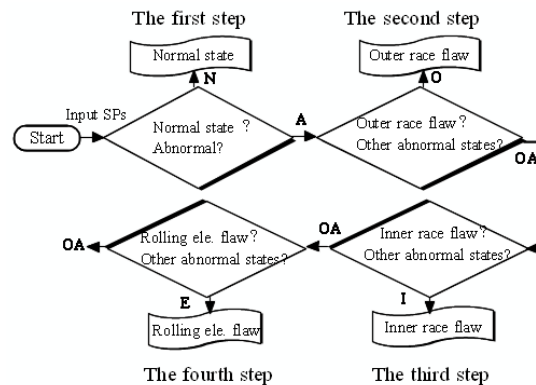


Fig. 3 Example for sequential diagnosis approach

### 3.2 Sensitivity evaluation for SP

Generally, the symptom parameters used for the condition diagnosis of plant machinery are selected by the following procedure [17].

(1) Measure the signals in normal state and each of the abnormal state using the sensors;

- (2) Define several symptom parameters;
- (3) Calculate the values of the symptom parameters using the obtained signals;
- (4) Check the sensitivity of each symptom parameter; if there are no adequate symptom parameters, return to step (2);
- (5) Then, adopt highly sensitive symptom parameters for fault diagnosis.

In order to evaluate the sensitivity of a SP for distinguishing two states, the distinction index ( $DI$ ) [4] is defined as follows:

$$DI = |\mu_1 - \mu_2| / \sqrt{\sigma_1^2 + \sigma_2^2} \quad (1)$$

where  $\mu_1, \mu_2$  are the mean values of the symptom parameter calculated by the data in state 1 and state 2, respectively, and  $\sigma_1$  and  $\sigma_2$  are their standard deviations. Here, the distinction rate ( $DR$ ) is calculated as follows:

$$DR = 1 - \left( \int_{-\infty}^{-DI} \exp\left(-\frac{u^2}{2}\right) / \sqrt{2\pi} du \right) \quad (2)$$

It is obvious that the larger the value of the  $DI$ , the larger the value of  $DR$  will be, and the better the symptom parameter will be. Therefore, the  $DI$  can be used to evaluate the sensitivity of the symptom parameter for distinguishing the states of machine. The  $DI$  is used for selecting the better symptom parameters for each sequential diagnosis step.

### 3.3 Verification by PNN

We also use the PNN to verify the efficiency of this diagnosis approach. Examples of fault diagnosis by the learned PNNs are shown in Table 1. According to the test results, the possibility grades output by the PNNs show the correct judgment in each state, and fault types can be sequentially and automatically distinguished by the sequential algorithm.

(a)	$p_5$	$p_8$	$g_N$	$g_A$	Judge
	4.389	3.544	0.985	0.014	$N$
	3.767	3.789	0.996	0.005	$N$
	96.62	57.99	0.011	0.988	$A$
	109.8	75.85	0.01	0.99	$A$

(b)	$p_6$	$p_7$	$g_O$	$g_A$	Judge
	0.881	6.875	0.921	0.011	$O$
	1.224	6.885	0.755	0.059	$O$
	1.378	8.125	0.000	0.999	$A$
	1.342	9.570	0.175	0.963	$A$

Table 1: Verification results (a) in the first step, (b) in the second step

## 4 Diagnosis approach by possibility theory and certainty factor model

Due to the complexity of plant machinery conditions, it is difficult to judge the relationship between fault states and the symptom parameters by a theoretical approach. Therefore, diagnostic knowledge is uncertain because the definite combination relationships between several symptoms and relevant machinery state cannot be easily obtained. In order to explain the uncertain

relationship, a diagnosis approach based on possibility theory and the certainty factor is proposed.

### 4.1 possibility theory

Possibility theory is used to solve the ambiguous problem of fault diagnosis [18]. The possibility function of the symptom parameter can be obtained from its probability density function [19-20]. For example, when the probability density function of the SP conforms to the normal distribution, it can be changed to a possibility function  $p(x_i)$  by

$$P(x_i) = \sum_{k=1}^N \min \{ \lambda_i, \lambda_k \} \quad (3)$$

$\lambda_i$  and  $\lambda_k$  can be calculated as follows:

$$\lambda_i = \int_{x_{i-1}}^{x_i} \frac{1}{\sigma\sqrt{2\pi}} \exp\left\{-\frac{(x-\mu)^2}{2\sigma^2}\right\} dx, \quad (4)$$

$$\lambda_k = \int_{x_{k-1}}^{x_k} \frac{1}{\sigma\sqrt{2\pi}} \exp\left\{-\frac{(x-\mu)^2}{2\sigma^2}\right\} dx$$

where,  $\sigma$  and  $\mu$  are the mean and standard deviation of the SP respectively, and  $x = \mu - 3\sigma \sim \mu + 3\sigma$ .

### 4.2 Certainty factor

The certainty factor ( $CF$ ) model was introduced as a method for representation and manipulation of uncertain knowledge in the rule-based expert system MYCIN. The certainty factor can handle the problem of a combination of heterogeneous data [21]. Therefore, in order to process the ambiguous relationship between symptom parameters and fault types, the combining possibility function of each state to be distinguished can be obtained by the MYCIN certainty factor. Practical examples should be shown in the later verification.

### 4.3 Verification

In the field of the condition diagnosis, it is important to first distinguish between the state of plant machinery in a normal state or abnormal state. In this stage, the abnormal state commonly includes two levels, namely, the caution level ( $C$ ) and the danger level ( $D$ ). The possibility function  $\mu_n(x)$  of the SP of the normal level can be easily calculated by (4) from the signal measured in the normal state. The possibility functions of the caution level and the danger level are expressed with  $\mu_c(x)$  and  $\mu_d(x)$ , respectively.  $\mu_c(x)$  and  $\mu_d(x)$  are calculated by

$$\mu_n(x) + \mu_c(x) + \mu_d(x) = 1$$

$$\mu_c /_{x \geq \mu + 3\sigma} = \text{Max}[\mu_c(x)], \quad (5)$$

$$\mu_c /_{x \geq \mu + 6\sigma \text{ and } x \leq \mu - 6\sigma} = 0, \mu_d /_{\mu - 3\sigma \leq x \leq \mu + 3\sigma} = 0$$

where  $\sigma$  and  $\mu$  are the mean value and the standard deviation of the SP calculated from the signal in the normal state, respectively.

The membership function of each level is shown in Fig.4 (a), and it is calculated beforehand and used for diagnosing the states of machinery.

If  $\mu_y(x_i)$  is the possibility function calculated from the data in the state to be diagnosed, the matching degrees with relevant level are calculated as follows:

$$w_{ni} = \int_{-\infty}^{\infty} \mu_n(x_i) \cdot \mu_y(x_i) dx_i$$

$$w_{ci} = \int_{-\infty}^{\infty} \mu_c(x_i) \cdot \mu_y(x_i) dx_i \quad (6)$$

$$w_{di} = \int_{-\infty}^{\infty} \mu_d(x_i) \cdot \mu_y(x_i) dx_i$$

where  $w_{ni}$ ,  $w_{ci}$ , and  $w_{di}$  express the possibility degree of a state in normal level, the caution level, and the danger level, respectively. These degrees are normalized by

$$w_{ni} + w_{ci} + w_{di} = 1 \quad (7)$$

The condition of machinery should be judged as the state where the value of the possibility degree is maximum.

In order to verify the diagnosis capability, all of the verification signals that are measured in the relevant known states had not been used for the pre-calculated membership function. The practical diagnosis example is shown in Fig.4 (b). Here,  $t_1$  is the possibility distributions of the SP that are calculated from the verification signals under the normal state.

The matching degrees (possibility degrees) of relevant state are obtained by (5)-(7), and the verification results are shown as follows:

- Possibility of the normal state (N):  $w_{ni}=77.48\%$ ;
- Possibility of the caution state (C):  $w_{ci}=22.49\%$ ;
- Possibility of the danger state (D):  $w_{di}=0.03\%$ .

Conclusion: the state can be judged as "Normal state".

According to the verification results, the condition of a bearing can be judged correctly.

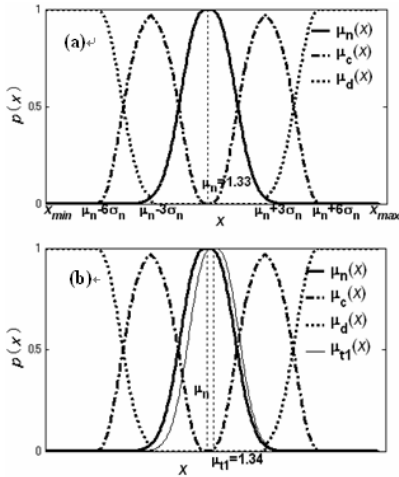


Fig. 4 Membership functions for the first diagnostic step (a) The pre-calculated membership function of each level, (b) Test example

## 5 Condition Diagnosis method based on adaptive filtering technique

This section introduces a diagnosis method using adaptive signal processing and fuzzy neural network for raising the accuracy of the fault diagnosis in reciprocating machine [22]. The flowchart of this diagnostic method is shown in Fig.5.

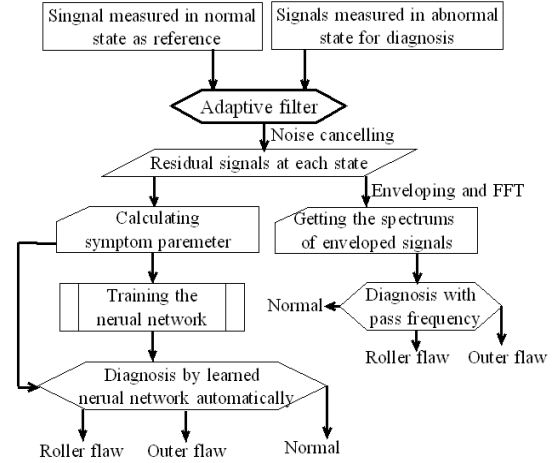


Fig. 5 Flowchart of fault diagnosis

### 5.1 Adaptive noise cancelling

Adaptive filters have been applied in signal processing and control, as well as in many practical problems [23]. 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.

An illustration for adaptive noise cancelling is shown in Fig. 6. 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  $N_r$ , 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  $\epsilon$  called residual signal.

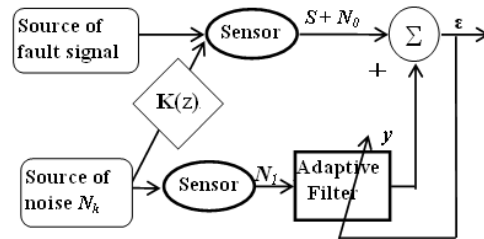


Fig. 6 Adaptive noise cancelling

### 5.2 Verification and discussion

In this case, roller bearings are utilized in a rice husking machine, and the simulated flaw is located at the roller and outer race of the rolling bearing for the tests of the condition diagnosis.

#### 5.2.1 Enveloped spectrum analysis

As an example, Fig.7 shows the enveloped signal spectrums under 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 clearly shows the peak at the pass frequency and exhibits many harmonics that correspond to the pass frequency. It is clearly evident that the bearing flaw can be detected more easily after adaptive filtering.

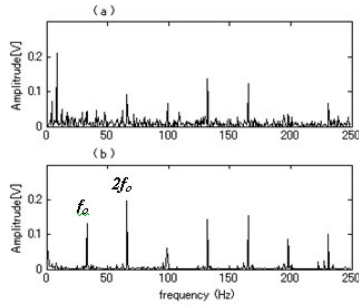


Fig. 7 Enveloped spectrums in outer flaw, (a) high-pass filtering, (b) adaptive filtering

### 5.2.2 Diagnosis by PNN

As input data of PNN, three symptom parameters in the time domain are considered [22]. Values of those symptom parameters are calculated using the signals with high-pass filtering 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 from the high-pass filtered signals are poor, and cannot discriminate the fault types. Contrarily, using the symptom parameters calculated with adaptive filtered signals, the neural network can get a good convergence.

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.

By these diagnosis results, this method is efficient for condition diagnosis of rolling bearing used in the reciprocating machine.

$P_1$	$P_2$	$P_3$	$N$	$O$	$R$	Judge
0.83	1.74	0.75	0.99	0.01	0.00	$N$
0.80	1.34	0.72	0.99	0.00	0.00	$N$
1.41	12.16	1.47	0.00	0.77	0.01	$O$
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	$R$
1.775	16.38	1.72	0.00	0.45	0.72	$R$

Table 2: Diagnosis results

## 6 Feature extraction method based on information theory

A method of feature extraction is proposed based on information theory [24]. The flowchart of this diagnosis approach is shown in Fig.8.

### 6.1 Obtaining method for a symptom parameter wave

To acquire the signal feature in the time domain, an obtaining method of the symptom parameter wave is proposed, as shown in Fig.9. The whole data of a discrete signal is divided into some smaller regions. The value of the symptom parameter can be calculated using the data in those regions. Connecting those points of the symptom parameter, the symptom parameter wave ( $SP(j), j=1\sim L$ ) can be derived.

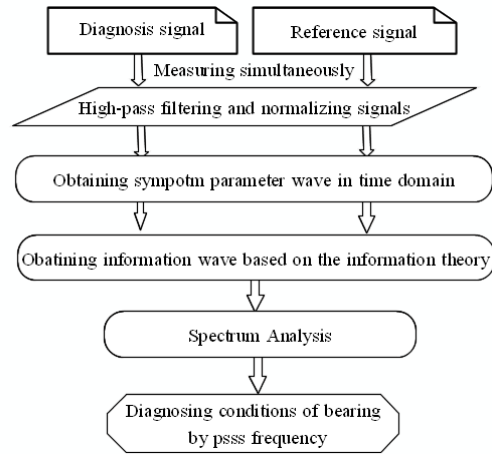


Fig. 8 Flowchart of diagnosis approach

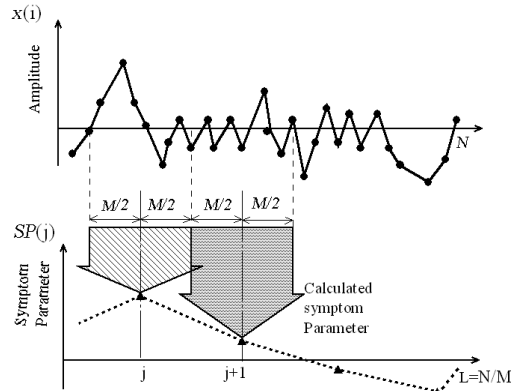


Fig. 9 Obtaining method of symptom parameter wave

### 6.2 Feature extraction by information theory

Kullback-Leibler divergence ( $KL$ ) plays a central role in the information theory of statistical inference. In case of fault diagnosis, the information theory had been applied for comparing the unknown distribution to be diagnosed with the known reference distribution. Those diagnosis method based on the information divergence has been used for the simple diagnosis of machinery [25-26]. However, its diagnostic capability for the precise diagnosis is lower. Information of a symptom parameter wave shortened as “information

wave” are proposed in the work based on the information theory.

An illustration for the derivation of the information waves ( $KL$  information wave:  $\Psi_{KL}$ ) is shown in Fig.10. Here, a symptom parameter wave  $SP_r(j)$  is calculated with the signal measured in the location to be diagnosed, and a symptom parameter wave  $SP_l(j)$  is calculated with the signal measured in the reference point which is faraway from the diagnosis position.

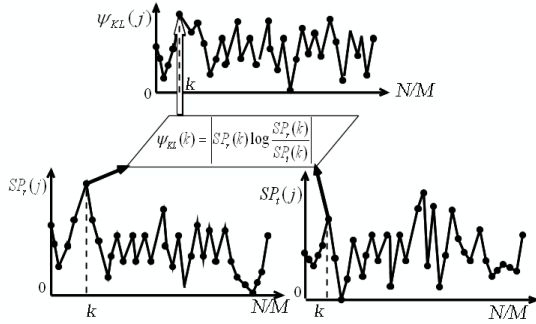


Fig. 10 Derivation of information wave

### 6.3 Spectral analysis for information wave

“Spectral difference of information wave” is used for identifying the fault types and is defined as follows.

$$Q_A^{KL}(f_i) = P_A^{KL}(f_i) - P_N^{KL}(f_i) \quad (8)$$

where, Spectral difference  $Q$  is a difference between spectral of information wave in the abnormal state and the normal state, and  $f_i$  is frequency of spectral.  $P_N$  and  $P_A$  are spectra of information wave in the normal state and the abnormal states, and can be obtained by FFT technique respectively.

### 6.4 Practical application

Practical diagnosis example for a bearing used in the diesel engine is given to verify the efficiency of this method.

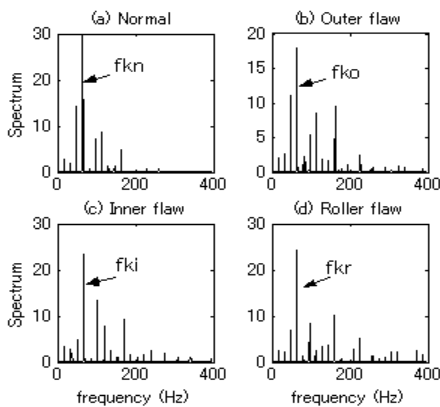


Fig. 11 Spectrums of enveloped diagnosis signal

Fig.11 shows the spectrums of enveloped diagnosis signal in each state after high-pass filtering with a 5 kHz cut-off frequency. The feature frequency ( $f_{ki}$ ,  $f_{ko}$ ,  $f_{kn}$  and  $f_{kr}$ ) in each state is the shock frequency of a piston. Fault frequency of bearing under abnormal states

cannot appear, and therefore, the fault types cannot be identified.

As examples, Fig.12 shows spectral differences of information waves  $Q_O(f_i)$  under the outer race flaw state. Fig.12 (a), (b) and (c) show  $Q_O^{KL}(f_i)$  of absolute mean value, root mean square, and shape of wave, respectively. Where,  $f_o$  is a pass-frequency of the outer race flaw. It is clearly evident that the outer flaw of a bearing can be detected easily by those spectral differences.

According to the verification results, the fault types of a bearing can be identified effectively. We also observed that the sensitivity of the different spectral differences of information waves is different.

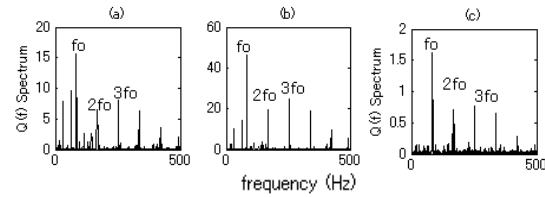


Fig. 12 Spectral differences of information waves with outer race flaw

## 7 Diagnosis method by time-frequency analysis in unsteady operating conditions

Time-frequency analysis [27] has proven to be an effective tool for analysing the behaviour of nonstationary signals. There are several time-frequency analysis methods, such as the short-time Fourier transform (STFT), wavelet analysis (WA), and the Wigner-Ville distribution (WVD), which may be used for condition diagnosis of rotating machinery in unsteady operating conditions. Many studies have been carried out with the goal of diagnosis of machinery condition. Those studies identify machinery faults by using the distribution of the spectrum in the time-frequency domain collectively, the symptom parameters are not considered, and the fault types cannot be identified automatically.

### 7.1 Feature spectra extracted by relative crossing information (RCI)

In this section, we propose a method for extracting the feature spectra from the time-frequency analysis techniques using the relative crossing information (RCI). The RCI is used to automatically extract the feature spectra from time-frequency analysis by computer in order to distinguish each state. The  $q_i(t)$  is the number of crossings over some level  $i$  of the vertical coordinate of the spectrum  $P(t, \omega)$  with a positive slope in unit time, and it can be calculated from the spectrum  $P(t, \omega)$ , shown as follows[28]:

$$q_i(t) = \frac{\sigma_v(t)}{2\pi\sigma_x(t)} \exp(-\{i/2\sigma_x(t)\}^2) \quad (9)$$

$$\sigma_x(t)^2 = \int_0^\infty P(t, \omega) d\omega, \sigma_v(t)^2 = \int_0^\infty (\omega)^2 P(t, \omega) d\omega \quad (10)$$

where  $P(t, \omega)$  is a spectrum calculated from the time signal by the time-frequency methods.

The vertical coordinate axis of a spectrum in the normal state is divided into  $M$  equal sections from maximum amplitude to minimum amplitude of the spectrum.  $q_{ni}(t)$  and  $q_{ai}(t)$  can be calculated by (9) in section  $i$  ( $i=1\sim M$ ) in the normal state and the state to be detected, respectively.

The RCI is expressed by the  $I_q(t)$  and is defined as

$$I_q(t) = \sum_{i=1}^M \left| \log \left( q_{ai}(t)/\overline{q_{ni}} \right) \cdot \left( q_{ai}(t) - \overline{q_{ni}} \right) \right| \quad (11)$$

where  $\overline{q_{ni}} = \frac{1}{T} \int_0^T q_{ni}(t) dt$  and  $T$  is the sampling time.

$I_q$  can be used to express the difference in spectra between the normal state and abnormal states, by which the feature spectra can be extracted in the time-frequency domain. Some real examples of  $I_q(t)$  (RCI) are shown in Fig.13.

We can extract the feature spectra of the outer flaw state in the position A-A where the value of  $I_q$  is maximum.

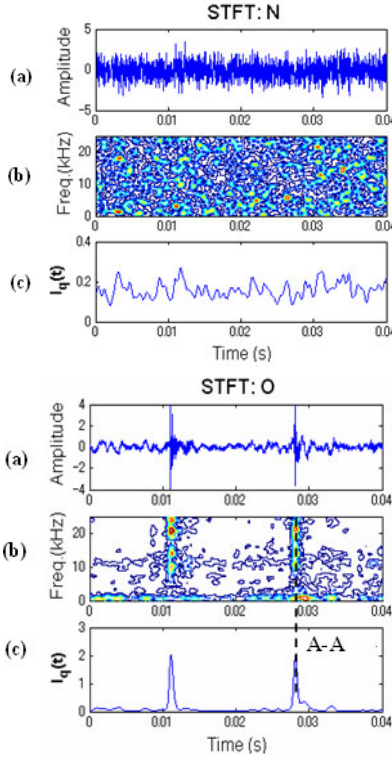


Fig. 13 Examples in normal state (N) and outer race flaw (O), (a) normalized signal, (b) the contour graphs of spectra processed by the STFT, (c) the RCI of spectra expressed by the  $I_q$ .

## 7.2 Synthesizing symptom parameter by least squares mapping (LSM)

After extracting the feature spectra by the RCI, the symptom parameters can be calculated using the feature spectra. In this section, in order to improve the diagnosis sensitivity, we propose a method by projecting the symptom parameters into discrimination space using least squares mapping [29]. The number of

symptom parameters ( $\mathbf{Y}_k$ ) is  $K$ , and the category number of states is  $M$ . In the coordinate space of  $K$  dimension, the endpoint of the vector  $\mathbf{Y}_{ij}$  expresses state  $i$ .  $\mathbf{Y}_{ij}$  is

$$\mathbf{Y}_{ij} = \{y_{ij1}, y_{ij2}, \dots, y_{ijK} \mid i=1 \sim M, j=1 \sim N_i\}^T \quad (12)$$

where  $N_i$  is the number of symptom parameters in the state  $i$ .

$\mathbf{Y}_{ij}$  can be projected into a new space  $\mathbf{L}$ , and the new vector  $\mathbf{L}_{ij}$  in the space  $\mathbf{L}$  can be calculated as follows:

$$\mathbf{L}_{ij} = \mathbf{A}\mathbf{Y}_{ij} \quad (13)$$

where  $\mathbf{L}_{ij} = \{l_{ij1}, l_{ij2}, \dots, l_{ijK} \mid i=1 \sim M, j=1 \sim N_i\}^T$ .

According to LMS algorithm, transformation matrix  $\mathbf{A}$  can be obtained as

$$\mathbf{A} = \left[ \sum_{i=1}^M \sum_{j=1}^{N_i} \{\mathbf{V}_i \mathbf{Y}_{ij}'\} \right] \left[ \sum_{i=1}^M \sum_{j=1}^{N_i} \{\mathbf{Y}_{ij} \mathbf{Y}_{ij}'\} \right]^{-1} \quad (14)$$

Fig.14 shows an illustration of the projection by the LSM, where  $K=2$  and  $M=2$ . Namely, the two states (state 1 and state 2) should be classified using two symptom parameter series.

According to the projected results shown in Fig.14 (b), the points in state 1 and state 2 are congregated to vector  $\mathbf{V}_1$  and  $\mathbf{V}_2$ , respectively. The two states in the space  $\mathbf{L}$  can be distinguished more easily than in the space  $\mathbf{Y}$ .

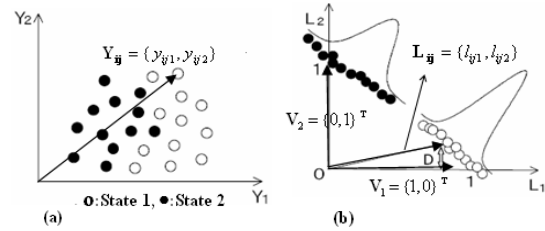


Fig. 14 Projected examples by the LSM, (a) Before projection, (b) After projection

## 7.3 Performance comparison of time frequency techniques

The performance of this approach is evaluated using three time-frequency transformation techniques. Fig.15 shows the flowchart for performance comparison.

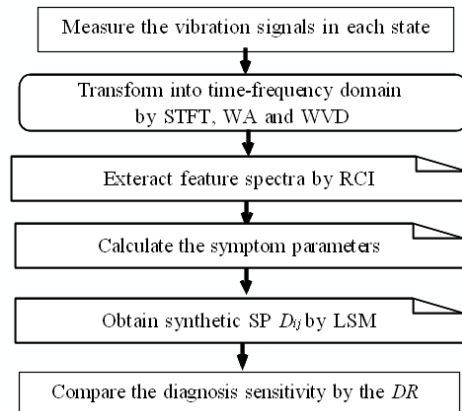


Fig. 15 Flowchart of performance comparison

In order to raise the diagnosis sensitivity of the symptom parameters, the new synthetic symptom parameter should be obtained by the LSM algorithm. In this case, the synthetic symptom parameter is defined as follows:

$$D_{ij} = \sqrt{(l_{i1} - 1)^2 + l_{i2}^2 + \dots + l_{i7}^2} \quad (15)$$

Fig.16 shows the values of the  $DR$  and  $DI$  of the synthetic symptom parameter in each diagnostic step by the time-frequency techniques. It is obvious that the diagnosis accuracy of the WVD is the best, because all of the  $DR$ s (or  $DI$ s) obtained by the WVD method are largest.

The calculation results of  $DI$  also show that the sensitivity of the new synthetic symptom parameter is higher than the original symptom parameters.

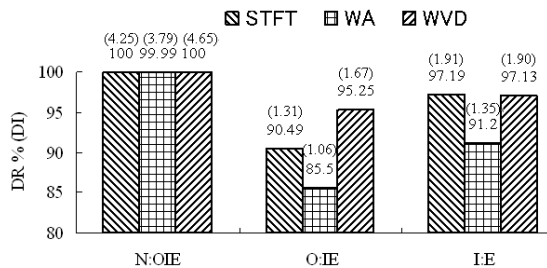


Fig. 16 Comparison result for the  $DR$  ( $DI$ ) of each method.

## 8 Conclusions

This paper reports several intelligent diagnostic approaches for rotating machinery based on artificial intelligence methods and feature extraction of vibration signals. Main conclusions are described as follows:

- (1) An intelligent method for condition diagnosis of rotating machinery was proposed, which constructed on the basis of the wavelet transform, the rough sets and the fuzzy neural network realized by the PNN. The wavelet transform performed to extract fault features of each state from measured signals to capture the true fault information across optimum frequency regions. Having the diagnosis knowledge acquired by the rough sets, the efficiency of NN learning was also improved, and the PNN accurately and quickly identified conditions of machine.
- (2) A fuzzy diagnostic method was also advanced, which was achieved through a sequential diagnostic approach and constructed on the basis of possibility theory, certainty factor and a fuzzy neural network. This diagnostic approach manipulated the ambiguous relationship between the symptom parameters and machinery conditions, and identified the states sequentially.
- (3) A diagnosis method was also adopted based on the adaptive signal processing technique for reciprocating machine. Diagnosis results showed that the diagnostic approach was very effective even for cancelling highly correlated noise, and for automatically discriminating the fault types.
- (4) A feature extraction method was present based on

the information theory. An obtaining method of a symptom parameter wave was defined, and a concept of spectral difference was derived. "Information wave" was also proposed by the information theory. By spectral difference of information wave, the feature spectra can be extracted clearly, and conditions of a machine can be discriminated effectively.

- (5) A new extraction method of feature spectra for rotating machinery in unsteady operation conditions was also proposed using the relative crossing information (RCI), by which the feature spectra from time-frequency analysis can be automatically extracted. The diagnosis sensitivities of three time-frequency analysis methods (STFT, WA, and WVD) were investigated for the condition diagnosis of machinery. The obtaining method of the synthetic symptom parameter was also projected by the Least-Squares Mapping (LSM) approach in order to improve the diagnosis sensitivity of the symptom parameter.

These proposed diagnostic methods had been successfully applied to condition diagnosis of practical rotating machinery, such as, a centrifugal pump, a centrifugal blower, reciprocating machine such as a diesel engine, etc.

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Huaqing WANG, email: wanghq\_buct@hotmail.com, School of Mechanical & Electrical Engineering, Beijing University of Chemical Technology, Beijing 100029, China.

\*corresponding author:

Peng CHEN, email: chen@bio.mie-u.ac.jp, Graduate School of Bioresources, Mie University, 1577 Kurimamachiya-cho, Tsu, Mie, 514-8507, Japan. Tle&Fax: +81-59-232-9594.