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Intelligent Methods for Condition Diagnosis of Plant Machinery

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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 (Lin et al, 2000) (Liu et al, 1999) (Matuyama, 1991) (Wang et al, 2007a). However, feature extraction for fault diagnosis is difficult because the vibration signals measured at any point of the machine often contain a strong noise.

Intelligent systems such as neural networks (NN) and support vector machine (SVM) have potential applications in pattern recognition and fault diagnosis. Many studies have been carried out to investigate the use of neural networks for automatic diagnosis of machinery, and most of these methods have been proposed to deal with discrimination of fault types collectively. However, the conventional neural network cannot reflect the possibility of ambiguous diagnosis problems, and will never converge when the first layer symptom parameters have the same values in different states. 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 (Pusey, 2000) (Mitoma et al, 2008) (Wang et al, 2008a).

For the above reasons, in order to process the uncertain relationship between symptom parameters and machinery conditions, and improve the efficiency and accuracy of fault diagnosis at an early stage, the authors reviewed their recent researches on intelligent diagnosis methods 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 in unsteady operating conditions; and the fault identification by support vector machine.

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 (Wang et al, 2008a) (Wang et al, 2007b). The flowchart of this approach is shown in Fig. 1.

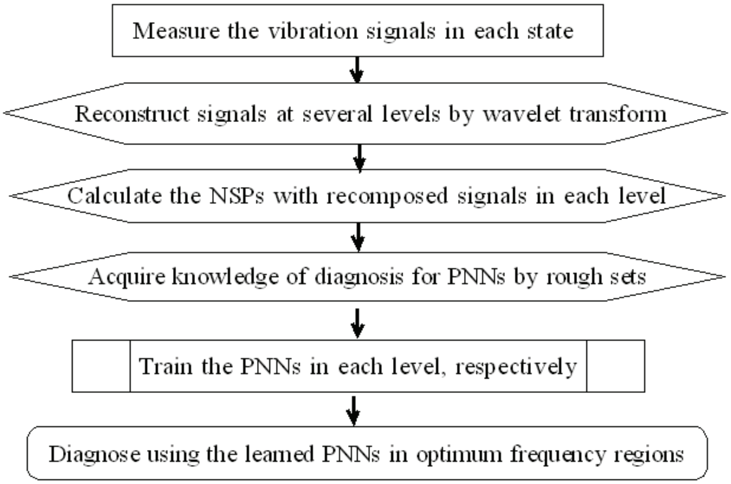


Fig. 1. Flowchart of intelligent diagnosis method

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 (Lin et al, 2000) (Liu et al, 1999). 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 (Mitoma et al,2008) (Wang et al, 2008a) (Wang et al, 2007b). 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 (Wang et al, 2008a).

2.3 Fuzzy neural network

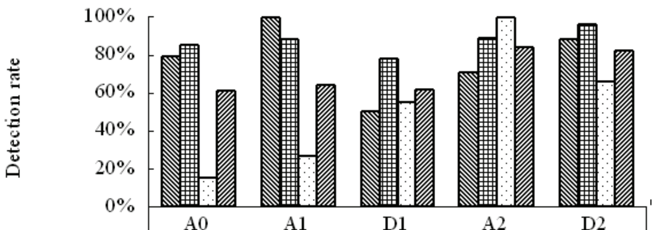
Although many studies have been carried out to investigate the use of NNs for automatic diagnosis of machinery condition, most of these methods have been proposed to deal with discrimination of fault types collectively (Saxena et al, 2007) (Samanta et al, 2003) (Li et al, 2006) (Alguindigue et al, 1993) (Samanta et al, 2006). 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 (Bishop , 1996).
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 detailed principle of the PNN had been described in (Wang et al, 2008a).

2.4 Knowledge acquisition by rough sets

Rough sets theory (Pawlak, 1991), a mathematical tool to deal with vagueness and uncertainty, has found many interesting applications. In this case, to 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.

2.5 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.



	A0	A1	D1	A2	D2
Normal	0.793	0.996	0.503	0.715	0.878
Cavitation	0.851	0.885	0.78	0.89	0.961
Misalignment	0.148	0.271	0.552	0.999	0.656
Unbalance	0.612	0.642	0.624	0.837	0.817

Level

Fig. 2. Parts of detection rates in each 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.

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 (Zhou et al, 2008). 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.

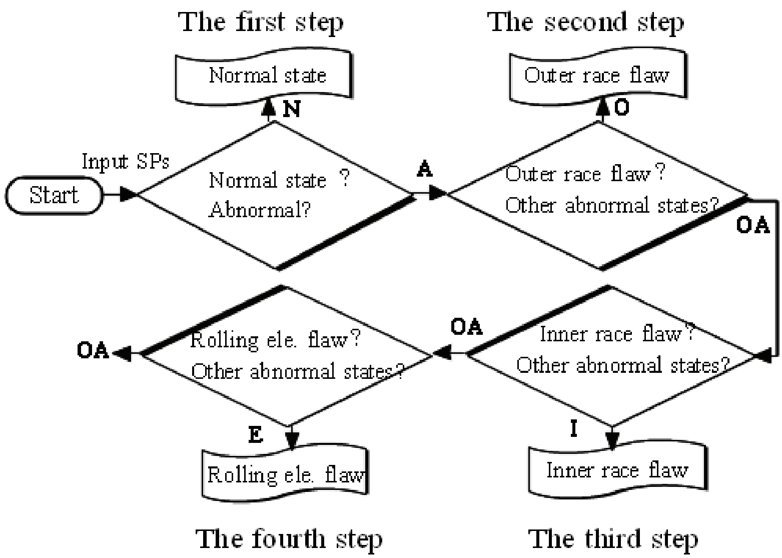


Fig. 3. Example for sequential diagnosis approach

3.2 Sensitivity evaluation for SP

Generally, the symptom parameters used for the condition diagnosis of plant machinery are selected by the following procedure (Pechon et al, 2007).

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*) (Wang et al, 2007) is defined as follows:

$$DI = |\mu_1 - \mu_2| \Big/ \sqrt{\sigma_1^2 + \sigma_2^2} \tag{1}$$

where μ_1, μ_2 are the mean values of the symptom parameter calculated by the data in state 1 and state 2, respectively, and σ_1 and σ_2 are their standard deviations. Here, the distinction rate (*DR*) is calculated as follows:

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

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. Part verification results for fault diagnosis are shown in Table 1.

(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

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.

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 types 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 (Chen et al, 2003). The possibility function of the symptom parameter can be obtained from its probability density function (Wang et al, 2008b) (Bendat, 1969). 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

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

λ_i and λ_k can be calculated as follows:

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

where, σ and μ 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 (Binaghi et al, 1998). 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 (*N*) or abnormal states. 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

$$\begin{aligned}&\mu_n(x)+\mu_c(x)+\mu_d(x)=1,\\&\mu_c\big/_{x=\mu\pm 3\sigma}=\mathrm{Max}[\mu_c(x)],\\&\mu_c\big/_{x\geq\mu+6\sigma\text{ and }x\leq\mu-6\sigma}=0,\ \mu_d\big/_{\mu-3\sigma\leq x\leq\mu+3\sigma}=0\end{aligned}\tag{5}$$

Where σ and μ 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:

$$w_{ni}=\int_{-\infty}^{\infty}\mu_n(x_i)\cdot\mu_y(x_i)dx_i,\ w_{ci}=\int_{-\infty}^{\infty}\mu_c(x_i)\cdot\mu_y(x_i)dx_i,\quad w_{di}=\int_{-\infty}^{\infty}\mu_d(x_i)\cdot\mu_y(x_i)dx_i\tag{6}$$

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

$$w_{ni}+w_{ci}+w_{di}=1\tag{7}$$

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

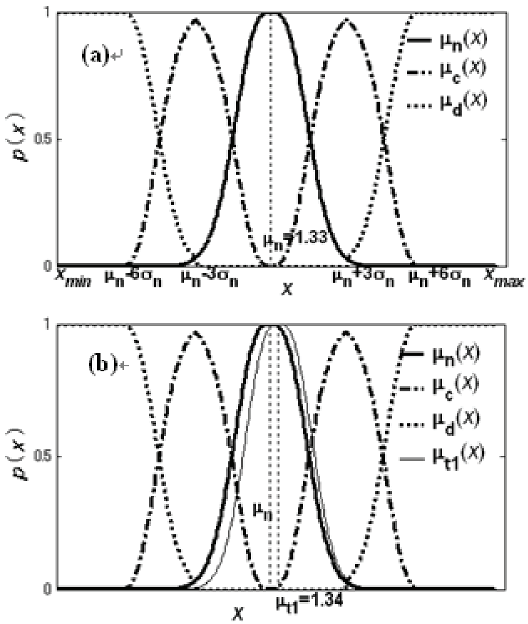


Fig. 4. Membership functions for the first diagnostic step (a) The pre-calculated membership function of each level, (b) Test example

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, t1 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 (Pusey, 2000) (Wang et al, 2008a), 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.

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 (Wang et al, 2008c). The flowchart of this diagnostic method is shown in Fig. 5.

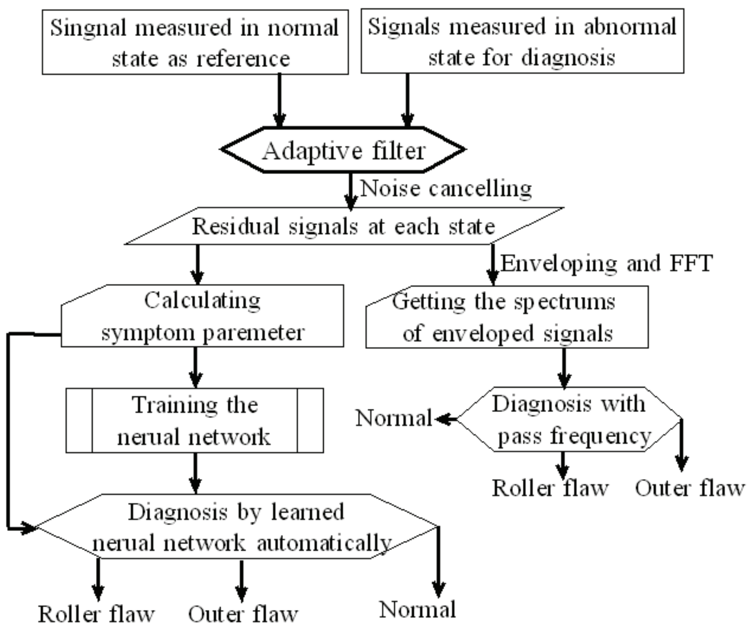


Fig. 5. Flowchart of fault diagnosis

5.1 Adaptive noise cancelling

Adaptive filters have been applied in signal processing and control, as well as in many practical problems (Alexander et al, 1986). 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 canceling 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_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.

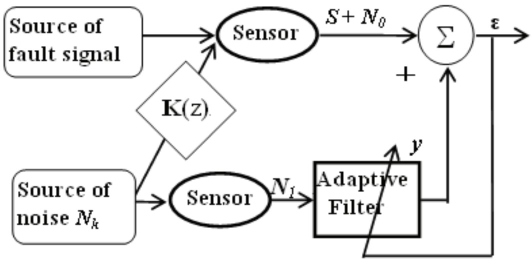


Fig. 6. Adaptive noise cancelling

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.

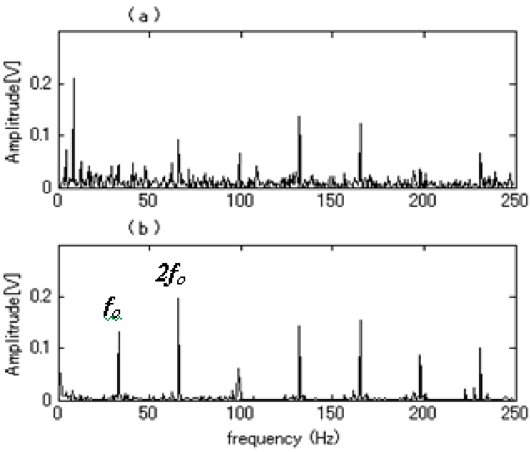


Fig. 7. Enveloped spectrums in outer-race flaw, (a) high-pass filtering, (b) adaptive filtering

5.2.2 Diagnosis by PNN

As input data of PNN, three symptom parameters in the time domain are considered (Wang et al, 2008c). 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 form 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.

P1	P2	P3	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 (Wang et al, 2007c) (Wang et al, 2009), and a flowchart of this diagnosis approach is shown in Fig. 8.

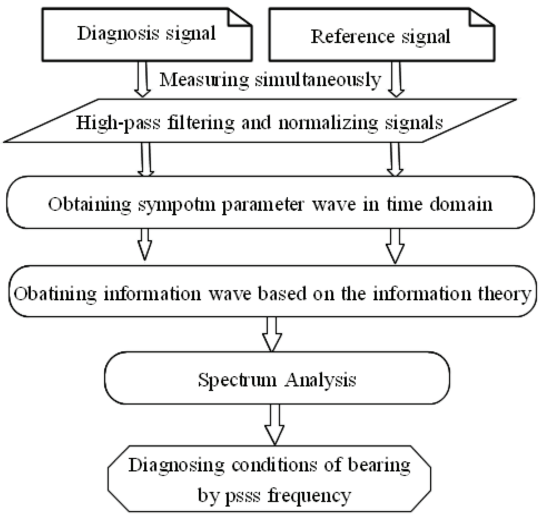


Fig. 8. Flowchart of diagnosis approach

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~L*) can be derived.

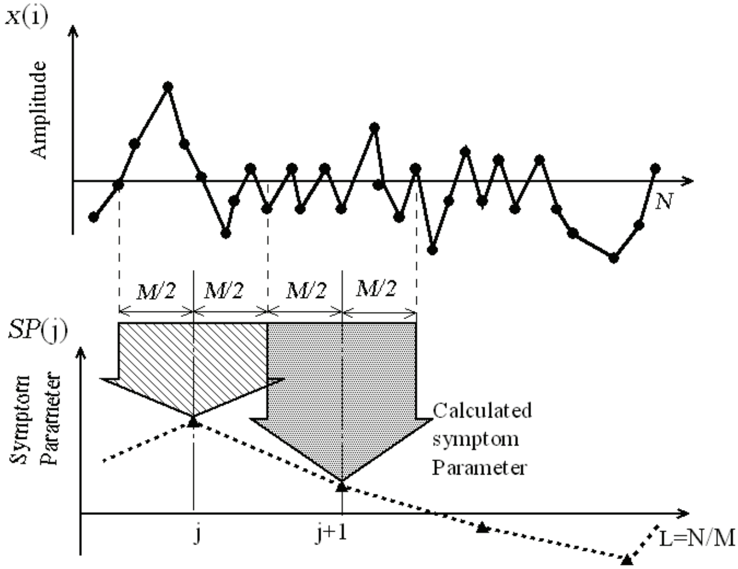


Fig. 9. A method to obtain a symptom parameter wave

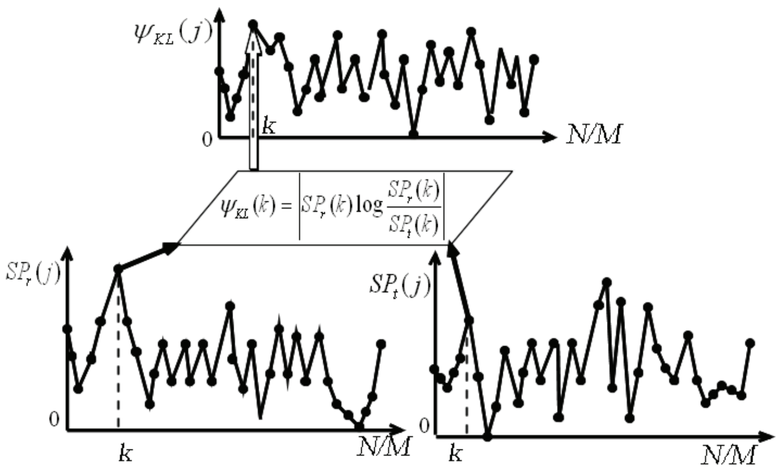


Fig. 10. Derivation of information wave

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 (Toyata et al, 1996) (Liu et al, 1996). 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: Ψ_{KL}) is shown in Fig. 10. Here, a symptom parameter wave $SP_t(j)$ is calculated with the signal measured in the location to be diagnosed, and a symptom parameter wave $SP_r(j)$ is calculated with the signal measured in the reference point which is faraway from the diagnosis position.

6.3 Spectral analysis for information wave

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

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

where, Spectral difference Q is a difference between spectral of information wave in the abnormal state and the normal state, and fi 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 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.

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

Time–frequency analysis (Cohen, 1995) 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.

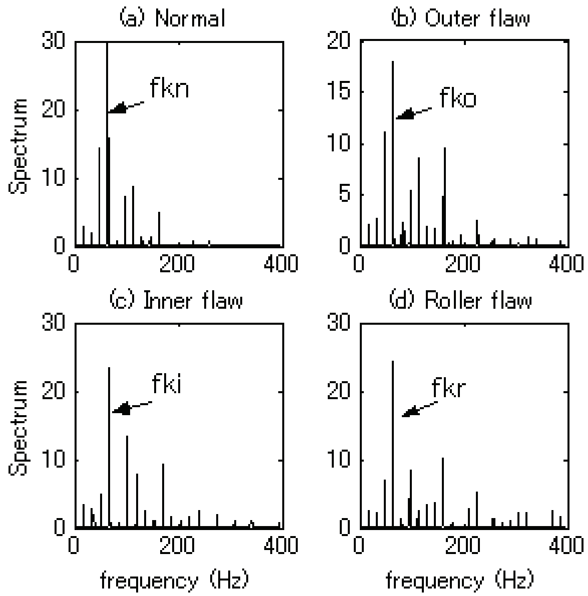


Fig. 11. Spectrums of enveloped diagnosis signal

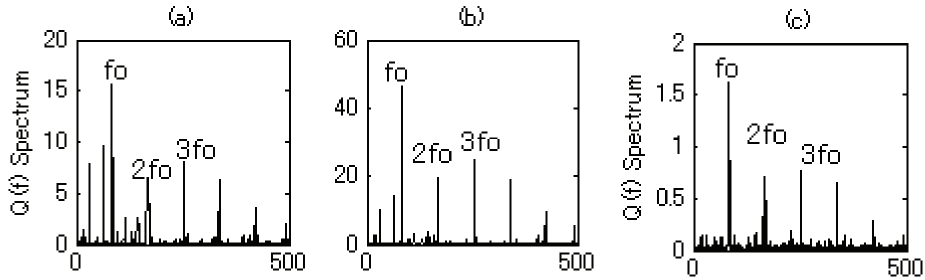


Fig. 12. Spectral differences of information waves with outer race flaw

This section introduces a method that is to integrate time-frequency analysis techniques with the automatic feature extraction method, sequential inference and possibility theory, and apply them to the condition diagnosis of a machine at the variable rotating speed (Wang et al, 2010a).

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,ω), shown as follows(Chen et al, 2001):

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

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

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

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

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.

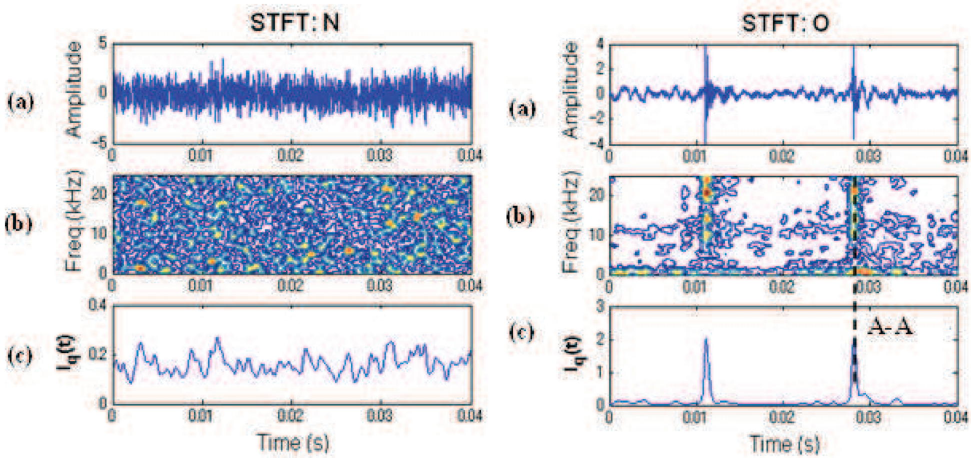


Fig. 13. Examples in normal state (N) and outer race flaw(O), (a) normalized signal, (b) the contour graphs of spectra processed by the STFT, (c) the RCI of spectra expressed by the *Iq*.

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 (Chen et al, 1995). The number of symptom parameters ($\boldsymbol{Y_k}$) is K, and the category number of states is M. In the coordinate space of K dimension, the endpoint of the vector $\boldsymbol{Y_{ij}}$ expresses state i. $\boldsymbol{Y_{ij}}$ is

$$\mathbf{Y_{ij}}=\left\{y_{ij1},y_{ij2},...,y_{ijK}\,\middle|\,i=1\sim M, j=1\sim N_i\right\}^T \tag{12}$$

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

$\boldsymbol{Y_{ij}}$ 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:

$$\mathbf{L_{ij}}=\mathbf{AY_{ij}} \tag{13}$$

where $\mathbf{L_{ij}}=\left\{I_{ij1},I_{ij2},...,I_{ijK}\,\middle|\,i=1\sim M, j=1\sim N_i\right\}^T$.

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

$$\mathbf{A}=\left[\sum_{i=1}^{M}\sum_{j=1}^{N_j}\left\{\mathbf{V_i Y'_{ij}}\right\}\right]\left[\sum_{i=1}^{M}\sum_{j=1}^{N_i}\left\{\mathbf{Y_{ij} Y'_{ij}}\right\}\right] \tag{14}$$

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 $\mathbf{Y}$.

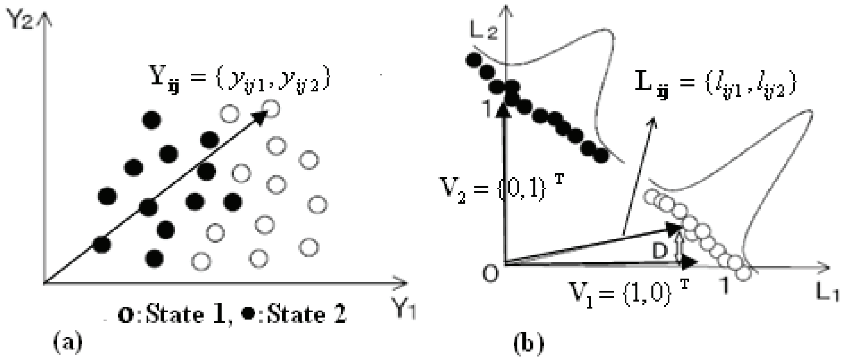


Fig. 14. Projected examples by the LSM, (a) Before projection, (b) After projection

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.

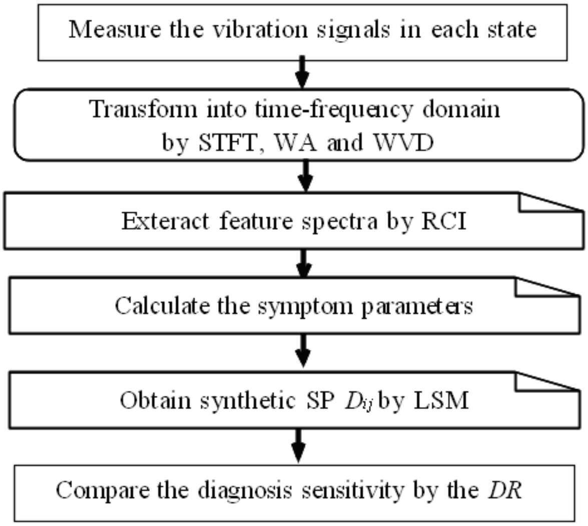


Fig. 15. Flowchart of performance comparison

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:

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

Fig. 16 shows the values of the D_R and D_I of the synthetic symptom parameter in each diagnostic stepby the time-frequency techniques. It is obvious that the diagnosis accuracy of the WVD is the best, because all of the D_{Rs} (or D_{Is}) obtained by the WVD method are largest. The calculation results of D_I also show that the sensitivity of the new synthetic symptom parameter is higher than the original symptom parameters.

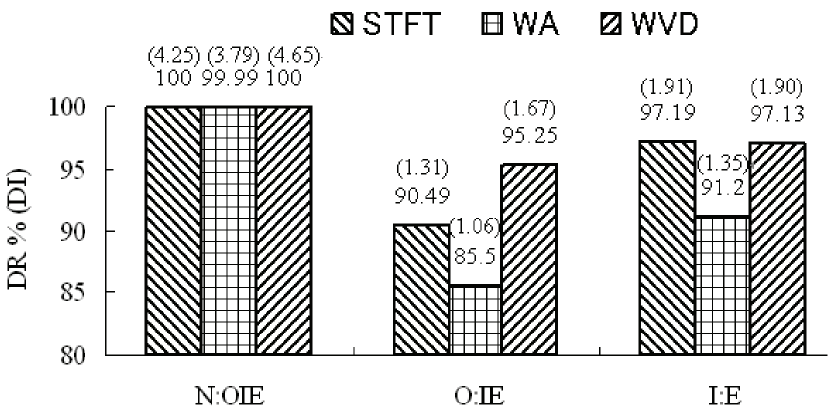


Fig. 16. Comparison result for the DR (DI) of each method.

8. Application of support vector machine in condition diagnosis

Most pattern recognition methods used in condition diagnosis of rotating machinery are studied that the sufficient samples are available. However, it is hard to obtain sufficient fault samples in practice. Support vector machine (SVM) can solve the learning problem with a small number of samples. This section reports a condition diagnosis method for a centrifugal blower using a multi-class classification technique, such as SVM to identify fault types. The statistic feature parameters are also acquired in the frequency domain for classification purposes, and those parameters can reflect the characteristics of vibration signals. The effectiveness of the method is verified by the application to the condition diagnosis for a centrifugal blower. The result shows that multi-class SVM produces promising results and has the potential for use in fault diagnosis of rotating machinery (Wang et al, 2010b).

8.1 Brief of support vector machine (SVM)

Support vector machine (SVM) is a relatively new computational learning method based on the statistical learning theory. SVM is based on Vapnik-Chervonenkis theory (VC-theory) that recently emerged as a general mathematical framework for estimating dependencies from finite samples. The basic idea of applying SVM to pattern classification can be stated as follows: first, map the inputs vectors into one features space, possible in higher space, either linearly or nonlinearly, which is relevant with the kernel function. Then, within the feature space from the first step, seek an optimized linear division, that is, construct a hyperplane which separates two classes. This technique can also be extended to multi-class classification. SVM training seeks a global optimized solution and avoid over-fitting, so it has the ability to deal with a large number of features (Wang et al, 2010b).
In the linear separable case, there exists a separating hyperplane whose function is

$$\mathbf{w} \cdot \mathbf{x} + b = 0 \tag{16}$$

which implies,

$$y_i(\mathbf{w} \cdot \mathbf{x} + b = 0) \geq 1, i = 1, \ldots, N \tag{17}$$

By minimizing $\|\mathbf{w}\|$ subject to this constrain, the SVM approach tries to find a unique separating hyperplane. Here $\|\mathbf{w}\|$ is the Euclidean norm of w, and the distance between the hyperplane and the nearest data points of each class is $2/\|\mathbf{w}\|$. By introducing Lagrange multipliers αi, the SVM training procedure amounts to solving a convex quadratic problem. The solution is a unique globally optimized result, which has the following properties,

$$w = \sum_i^N \alpha_i y_i \mathbf{x}_i \tag{18}$$

Only if corresponding $a_i > 0$, these x_i are called support vectors.
When SVM are trained, the decision function can be written as

$$f(\mathbf{x}) = sign(\sum_i^N \alpha_i y_i (\mathbf{x} \cdot \mathbf{x}_i) + b) \tag{19}$$

For a linear non-separable case, SVM performs a nonlinear mapping of the input vector x from the input space RN into a higher dimensional Hilbert space, where the mapping is determined by kernel function. According to the different classification problems, the different kernel function can be selected to obtain the optimal classification results (Widodo et al, 2009).

8.2 Practical application

Practical diagnosis example for a bearing used in a centrifugal blower is given to verify the efficiency of this method. The diagnosis approaches are shown as follows. A high-pass filter with a 5 kHz cut-off frequency was used to cancel noise from the measured signals. The filtered signals were processed by the Hilbert-Huang Transform, and the spectra of the enveloped waveforms were obtained by the FFT. Then, the feature parameters were calculated with the envelope spectra, and used for SVM classification. Lastly, fault diagnosis was carried out by the SVM. In this study, seven of these parameters (Wang et al, 2010b) in frequency domain, commonly used for the fault diagnosis of plant machinery, are acquired for classification purposes.

The number of train samples and the number of test samples in each state are 10. The optimized kernel parameters, C and γ are 1.533 and 3.526, respectively. We used which data measured in each state had not been trained by the SVM in order to verify the diagnostic capability of the SVM. The training results and test results are shown in Figs. 17 and 18. In Fig. 17 and 18, class 1, 2, 3 and 4 mean normal, inner-race flaw, and outer-race flaw and roller-race flaw states, respectively. In this case, the test accuracy is 100%, and the test error is zero.

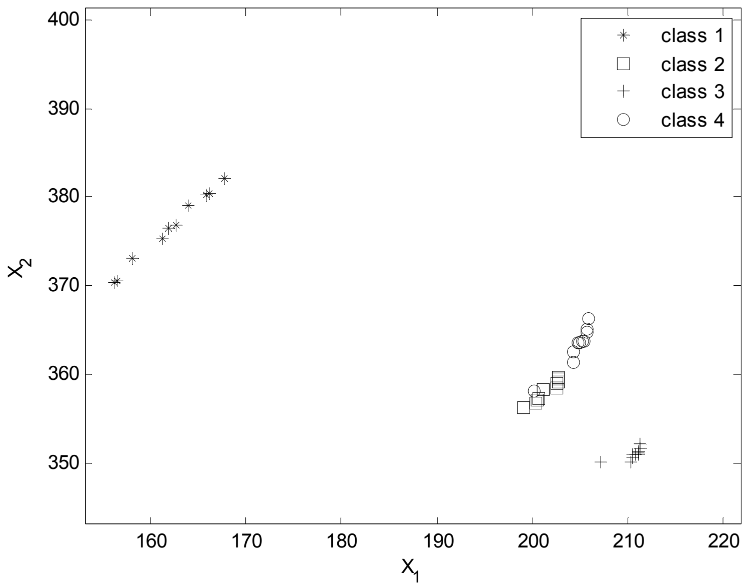


Fig. 17. Training result

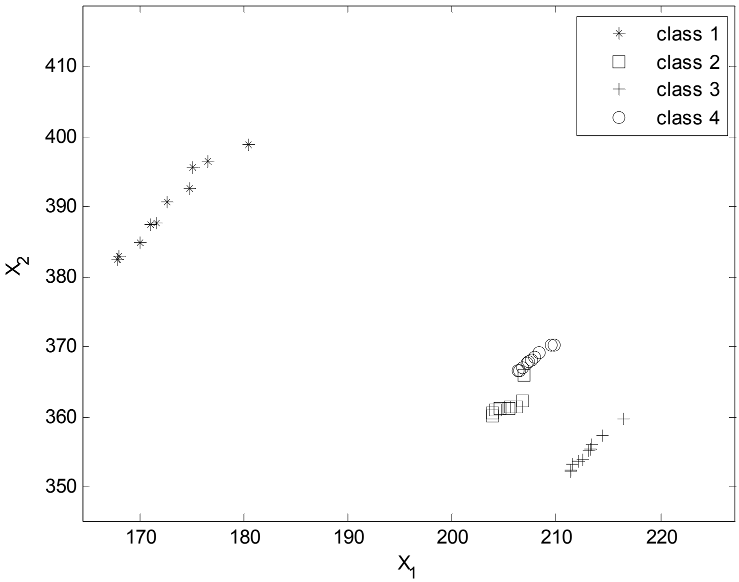


Fig. 18. Test result

The classification results show that the multi-class LS-SVM can identify the fault types with high accuracy, and SVM has the potential for use in fault diagnosis of rotating machinery.

9. Conclusion

This chapter reported 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.
6. A condition identification method for a centrifugal blower was proposed using a multi-class classification technique, such as SVM. The effectiveness of the method is verified by the application to the condition diagnosis for a centrifugal blower. The result shows that the multi-class SVM produces promising results and has the potential for use in fault diagnosis of rotating machinery.

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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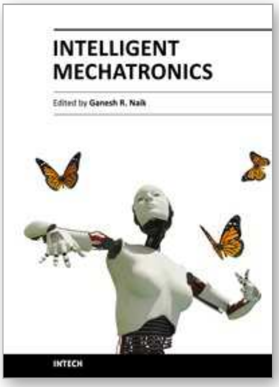

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This book is intended for both mechanical and electronics engineers (researchers and graduate students) who wish to get some training in smart electronics devices embedded in mechanical systems. The book is partly a textbook and partly a monograph. It is a textbook as it provides a focused interdisciplinary experience for undergraduates that encompass important elements from traditional courses as well as contemporary developments in Mechtronics. It is simultaneously a monograph because it presents several new results and ideas and further developments and explanation of existing algorithms which are brought together and published in the book for the first time.