Condition Diagnosis of Blower System Using Rough Sets and a Fuzzy Neural Network

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Abstract: **-** This paper presents a condition diagnosis method for a blower system using the rough sets, and a fuzzy neural network to detect faults and distinguish fault types. In order to solve the ambiguous problem between the symptoms and the fault types, the diagnosis knowledge for the training of the neural network is acquired by using the rough sets. The fuzzy neural network realized by partially-linearized neural network (PNN), which can automatically distinguish the faults. The PNN can quickly converge when learning, and can quickly and high-accurately distinguish fault types on the basis of the probability distributions of the machine conditions when diagnosing. The non-dimensional symptom parameters are also defined in frequency domain, and those parameters are processed by rough sets to sensitively diagnose machinery conditions. Practical examples of the diagnosis for a blower system are shown in order to verify the efficiency of the method proposed in this paper.

Key-Words: **-** Condition diagnosis, Fuzzy neural network, Rough sets, Symptom parameter, Blower

1 Introduction

In the field of machinery diagnosis, vibration analysis is often used for detection of mechanical fault and discrimination of fault types. Condition diagnosis of rotating machinery 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, in the case of condition diagnosis of rotating machinery, knowledge of distinguishing fault is ambiguous, and definite relationships between symptoms and fault types cannot be easily identified. There are two main reasons for this. (1) The effect of noise in the vibration signal measured for fault detection may be so strong that the symptom of a fault in the rotating machinery is not evident. (2) The statistical objectivity of the measured signal cannot always be satisfied because of the measuring techniques and manner of the inspectors [5].

Although many studies [6]-[9] have been carried out to investigate the use of neural networks (NN) for automatic diagnosis of machine conditions, the conventional NN cannot adequately reflect the possibility of ambiguous diagnosis problems. The NN will never converge when the first-layer symptom parameters have the same values in different states [10].

For the above reasons, we propose a condition diagnosis method for a blower using the rough sets and a neural network to detect faults and distinguish fault types. Fig. 1 shows the flowchart of the intelligent diagnosis method. The vibration signals of a blower are measured in each state, and the high frequency noises are cancelled with a low-pass filter. The symptom parameters in frequency domain are calculated with the spectrums of the signals for feature extraction. The diagnostic knowledge for the training of the fuzzy neural network is acquired by using the rough sets [11] [12]. The fuzzy neural network, having learnt the diagnostic knowledge from the rough sets, can represent complex relationships between faults and symptoms; these are difficult to model with traditional physical methods. Practical examples of the condition diagnosis for a blower system are shown to verify the method's efficiency.

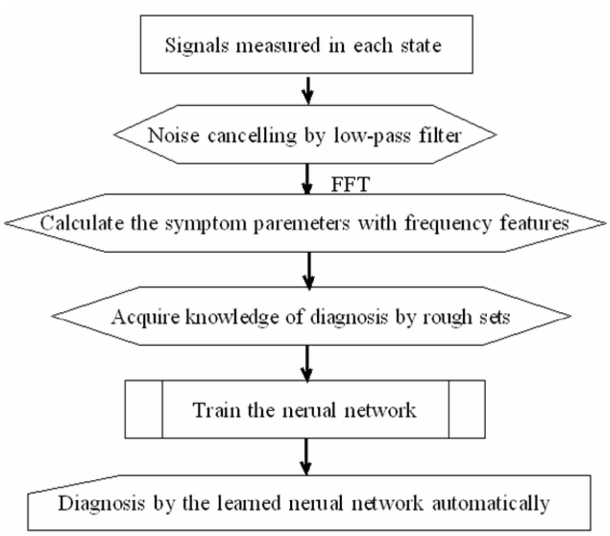


Fig. 1 Flowchart of the diagnosis method

2 Blower System and Preprocessing

The blower for condition diagnosis is shown in Fig. 2. The motor is employed to drive the blower through a belt, and the rotation speed can be varied by a speed controller. As shown in Fig. 3(a), two acceleration sensors are used to measure vibration signals for the condition diagnosis, and the sensors are mounted on the bearing housing at the end of the blower shaft in vertical and horizontal directions respectively. The sampling frequency of the signals is 100 kHz for each channel, and the sampling time is 10 sec. As the blower usually works at a constant speed, the vibration signals are measured at a rotation speed of 800 rpm, and the start-up and stop-down process are not under consideration.

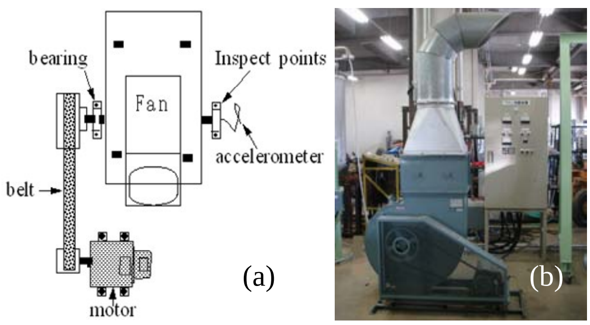


Fig. 2 The blower system for condition diagnosis (a) Illustrate of the blower system, (b) The blower system in the field

Three types of faults, such as the impeller unbalance, the bearing housing looseness, and the belt looseness often occurring in a blower machine, are considered in this work. The unbalance fault and the bearing housing looseness are shown in Fig. 3. Here, the original signal are divided into 30 signal parts for acquiring the knowledge for the learning of the PNN, and the sampling time of per signal part is 0.33s (4.4 shaft rotations).

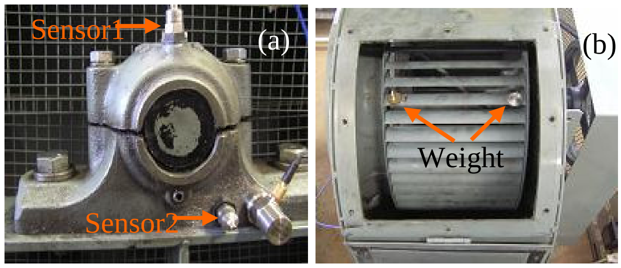


Fig. 3 Faults and location of Sensors (a) Bearing housing looseness, (b) Unbalance (with two weights (2×20g))

Since those faults belong to the structural faults and appear in the low frequency domain, a low-pass filter with 100 Hz cut-off frequency is used to cancel the high frequency noise in the vibration signals. The power spectrums of the signals can be obtained by FFT, and be used for the calculation of the symptom parameters. The filtered signals and examples of the power spectrums in each state are shown in Fig.4 and Fig.5 respectively.

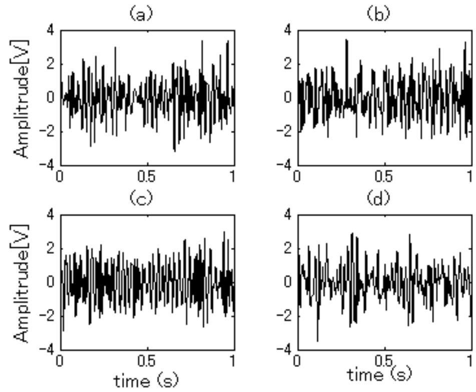


Fig. 4 The signals after low-pass filtering (a) Normal, (b) Unbalance, (c) Bearing housing looseness, (d) Belt looseness

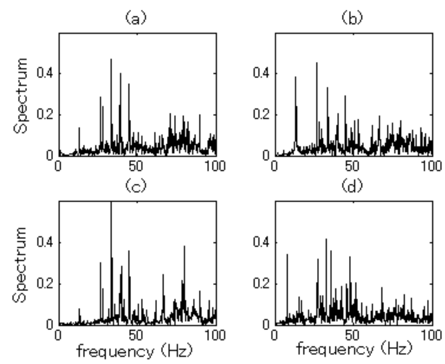


Fig. 5 The power spectrums waveform (a) Normal, (b) Unbalance, (c) Bearing housing looseness, (d) Belt looseness

3 Symptom Parameters for Condition Diagnosis

For automatic diagnosis, the symptom parameters (SP) are needed that can sensitively distinguish the fault types. A large set of symptom parameters has been defined in the pattern recognition field [13] [14]. In this study, seven of these parameters in frequency domain, commonly used for the fault diagnosis of plant machinery, are considered.

$$p_1 = \sqrt{\frac{\sum_{i=1}^{N} f_i^2 \cdot S(f_i)}{\sum_{i=1}^{N} S(f_i)}} \quad (1)$$

$$p_2 = \sqrt{\frac{\sum_{i=1}^{N} f_i^4 \cdot S(f_i)}{\sum_{i=1}^{N} f_i^2 \cdot S(f_i)}} \quad (2)$$

$$p_3 = \frac{\sum_{i=1}^{N} f_i^2 \cdot S(f_i)}{\sqrt{\sum_{i=1}^{N} S(f_i) \sum_{i=1}^{N} f_i^4 \cdot S(f_i)}} \quad (3)$$

$$p_4 = \frac{\sigma}{\overline{f}} \quad (4)$$

$$p_5 = \frac{\sum_{i=1}^{N} (f_i - \overline{f})^3 \cdot S(f_i)}{\sigma^3 \cdot N} \quad (5)$$

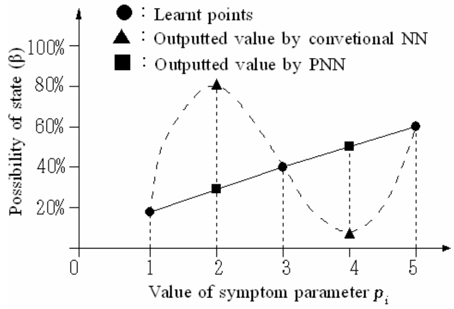
$$p_6 = \frac{\sum_{i=1}^{N} (f_i - \overline{f})^4 \cdot S(f_i)}{\sigma^4 \cdot N} \quad (6)$$

$$p_7 = \frac{\sum_{i=1}^{N} \sqrt{|f_i - \overline{f}|} \cdot S(f_i)}{\sqrt{\sigma} \cdot N} \quad (7)$$

where, N is the number of spectrum line, f_i is the frequency and from 0 Hz to 100 Hz in this work, $S(f_i)$ is the power spectrum of waveform, $\sigma = \sqrt{\frac{\sum_{i=1}^{N} (f_i - \overline{f})^2 \cdot S(f_i)}{N-1}}$ and $\overline{f} = \sum_{i=1}^{N} f_i \cdot S(f_i) \Big/ \sum_{i=1}^{N} S(f_i)$.

4 Partially-linearized Neural Network

In the case of a conventional neural network (NN) built for pattern recognition in fault diagnosis, the factors entered into the input (1st) layer of the network are several features or symptom parameters. Each unit in the last layer exclusively outputs two values (1 or 0) to express categories of pattern (or state) [15]-[17]. Though the value between 0 and 1 may appear in the output layer when executing a learnt NN, it is difficult to accurately explain the meaning of the value as a result of the pattern recognition or condition diagnosis. To illustrate this fact, Fig. 6 shows a simple example for identifying the possibility of state (β) with one symptom parameter p_i. If NN has learned the values of the training data shown by point ●, it will output nonlinear values shown by ▲. In order to improve this unreasonable result, we partially linearized the nonlinear part in the NN and describe it as a "Partially-linearized neural network (PNN)". In Fig. 6, the PNN outputs the linear values, shown by ■, according to the learned points, shown by ●.



The case of non-linear (Conventional NN)

		p_j	β
●	Learning	1	20%
▲	Diagnosis	2	80%
●	Learning	3	40%
▲	Diagnosis	4	10%
●	Learning	5	60%

The case of linear (PNN)

		p_j	β
●	Learning	1	20%
■	Diagnosis	2	30%
●	Learning	3	40%
■	Diagnosis	4	50%
●	Learning	5	60%

Fig. 6 A simple example for comparing NN with PNN

In the field of condition diagnosis of plant machinery, the relationships between faults and symptoms are complex and difficult to model mathematically with traditional physical methods. The PNN can learn the knowledge acquired by the rough sets shown in next chapter, after which the PNN can automatically distinguish each state when the value of the symptom parameters is inputted. Here, the basic principle of the PNN for the fault diagnosis is described as follows.

The neuron number of the mth layer of the NN is N_m. The set $X^{(1)} = \{X_i^{(1,j)}\}$ represents the pattern inputted to the 1st layer and the set $X^{(M)} = \{X_i^{(M,k)}\}$ is the training data for the last layer (Mth layer).

where, $X_i^{(1,j)}$: the value inputted to the jth neuron in the input (1st) layer; $X_i^{(M,k)}$: the output value of the kth neuron in the output (Mth) layer, $i = 1$ to P, $j = 1$ to N_1, $k = 1$ to N_M and $k = 1$ to N_M.

Even if the NN converges by learning $X^{(1)}$ and $X^{(M)}$, it cannot deal well with the ambiguous relationship between the new $X^{(1)*}$ and $X^{(M)*}$, which had not been learned. In order to predict $X^{(M)*}$ according to the probability distribution of $X^{(1)*}$, a partially linear interpolation of the NN is introduced in Fig. 7 as "PNN".

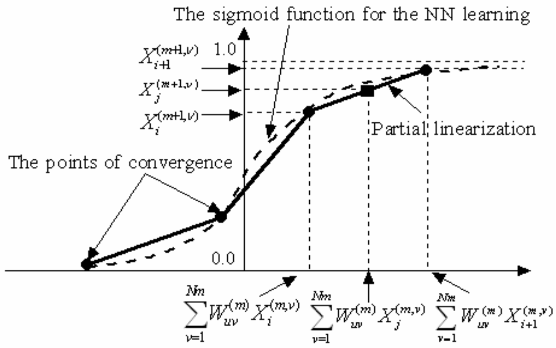


Fig. 7 The partial linearization of the sigmoid function

In the PNN that has converged by the training data $X^{(1)}$ and $X^{(M)}$, the symbols are used as follows.

$X_i^{(m,t)}$: The value of the *t*th neuron in the hidden (*m*th) layer; $t = 1$ *to* N_m.

$W_{uv}^{(m)}$: The weight between the *u*th neuron in the *m*th layer and the *v*th neuron in the (*m+1*)th layer; $m = 1$ *to* $M; u = 1$ *to* $N_m; v = 1$ *to* N_{m+1}.

If these values are all remembered by the computer, then when new values $X_j^{(1,u)*}$ ($X_i^{(1,u)} < X_j^{(1,u)*} < X_{i+1}^{(1,u)}$) are inputted to the first layer, the predicted value of the *v*th neuron (*v=1* to N_m) in the (*m+1*)th layer (*m=1* to *M-1*) will be estimated by

$$X_j^{(m+1,v)} = X_{i+1}^{(m+1,v)} - \frac{\{\sum_{u=1}^{Nm} W_{uv}^{(m)}(X_{i+1}^{(m,u)} - X_j^{(m,u)})\}(X_{i+1}^{(m+1,v)} - X_i^{(m+1,v)})}{\sum_{u=1}^{Nm} W_{uv}^{(m)}(X_{i+1}^{(m,u)} - X_i^{(m,u)})} \quad (8)$$

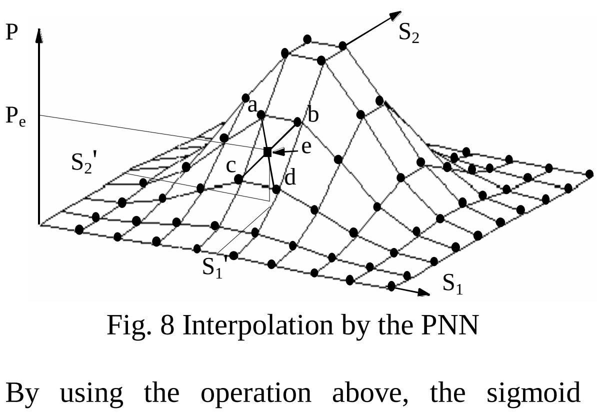


Fig. 8 Interpolation by the PNN

By using the operation above, the sigmoid function is partially linearized, as shown in Fig. 7. If a function must be learned, the PNN will learn the points indicated by the symbols (●) shown in Fig. 8. When new data (s_1', s_2') are inputted into the converged PNN, the value indicated by the symbols (■) corresponding to the data (s_1', s_2') will be quickly identified as P_e. Thus, the PNN can deal with ambiguous diagnosis problems.

5 Knowledge Acquisition by Rough Sets

Rough set theory, a mathematical tool to deal with vagueness and uncertainty, has found many interesting applications. The rough set approach is of fundamental importance to AI and cognitive sciences, especially in the areas of machine learning, knowledge acquisition, decision analysis, and knowledge discovery from databases [11] [12].

To diagnose machine states accurately, decrease the number of parameters inputting into the PNN, and increase the efficiency of the PNN learning, rough sets are used to acquire diagnosis knowledge. The values of symptom parameters ${}^j p_{ls} \cdots {}^j p_{ms}$ can be calculated by the power spectrums of the signals. Here, *j=1* to *J*, and *J* is the total number of measurements for the acquisition of the diagnosis knowledge. The ${}^j p_{is}$ must be digitized as the teacher data for the PNN by the following formula:

$${}^j p_{is} = 0 \text{ to } A_{pi} = \text{int}[{}^j p_{is} / \{(\max\{{}^j p_{is}\} - \min\{{}^j p_{is}\}) / N_{pi}\} + 1] \quad (9)$$

Here, int[*] is the function which gives the integral values of *.

$$p = \{p_1, p_2, \cdots, p_m\} \quad (10)$$

is the initial symptom parameter set (mentioned in section 3). ${}^j p_S$ is the set of symptom parameter values measured in the state *S*.

$${}^j p_S = \{{}^j p_{1S}, {}^j p_{2S}, \cdots, {}^j p_{mS}\} \quad (11)$$

[${}^j p_{is}$] is defined as follows

$$r_k = [{}^k p_{is}] = \{{}^k p_{is} | {}^x p_{is} \ \& \ {}^y p_{is} \in [{}^k p_{is}] \rightarrow {}^x p_{is} = {}^y p_{is}\} \quad (12)$$

The symptom parameters set P_{ij}, which is selected from *P* and shown in (10), can discriminate between r_i and r_j:

$$P_{ij} = \{p_k \mid p_k \in P; \ p_k^* \text{ is the value of } p_k; \ p_k^* \in r_i \text{ or } p_k^* \in r_j \rightarrow p_k^* \in (r_i \cup r_j) - (r_i \cap r_j)\} \quad (13)$$

For distinguishing r_i (*i*=1 to *Q*) from r_j (*j*=1 to *Q*, $j \neq i$), there may be redundant SPs in the initial set *P* shown in (10). In order to remove the redundant SPs, the following algorithm is proposed:

(a) Remove p_i from *P*;

(b) Calculate P_{ij} as shown in (13);

(c) If $P_{ij} \neq \Phi$ (empty set), then p_i is the redundant SP. Remove p_i from *P*. Return to (a) and repeat from (a) to (c) and from *i*=1 to *i* =*Q*;

(d) After removing all redundant SPs, the new set of SPs $p' = \{p_1, p_2, \cdots, p_l\}$ $(l \leq m)$ is obtained and the value set of P' of r_i is : ${}^{ri}p'$.

$$ {}^{ri}p' = \{ {}^{ri}p_{1s}, {}^{ri}p_{2s}, \cdots {}^{ri}p_{ls} \} \tag{14} $$

The possibility ${}^{s}\beta_{ri}$ of state S expressed by r_i can be calculated by

$$ {}^{s}\beta_{ri} = \frac{card({}^{S}r_j)}{card(r_j)} \% \tag{15} $$

Here, *card (r)* is the element number of *r*. ${}^{S}r_j \in {}^{ri}p'$ is r_j obtained from state *S*.

According to the principle above, the input data and teacher data (diagnosis knowledge) for the PNN are as follows:

Input data are the value sets ${}^{ri}p'$ of SPs of r_i, from which redundant SPs have been removed.

Teacher data are the possibility ${}^{s}\beta_{ri}$ of state *S*.

6 Diagnosis and Verification

Vibration signals measured in each state are preprocessed by low-pass filter with the cut-off frequency of 100 Hz. The symptom parameters are calculated in frequency domain by (1)-(7), and are digitized by (9) for the rough sets. The redundant symptom parameters removed by using the rough sets algorithm shown in section 5. Table 1 marked the redundant symptom parameters with "×".

Table 1 Redundant Symptom Parameters

p_1	P_2	p_3	p_4	p_5	p_6	p_7
O	×	×	×	O	O	×

Fig. 9 shows the PNN built based on the method proposed in this paper. It consists of the first layer, one hidden layer and the last layer. The neurons in the first layer are the inputted symptom parameters (p_1, p_5 and p_6) processed by the rough sets. The outputs in the last layer are ${}^{N}\beta_{ri}$, ${}^{U}\beta_{ri}$, ${}^{B}\beta_{ri}$, and ${}^{L}\beta_{ri}$, which are the possibility grades of the normal state, the unbalance state, the bearing housing looseness state and the belt looseness state, respectively.

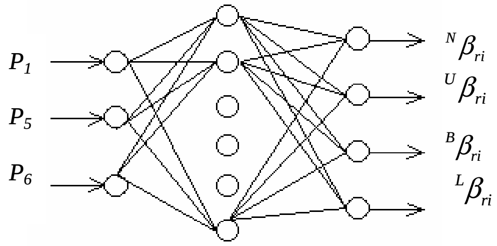


Fig. 9 Paritially-linearized neural network

The diagnosis knowledge for the PNN is acquired by the rough sets, (parts of data are shown in Table 2). By learning the knowledge, the PNN can quickly diagnose those faults with the possibility grades ${}^{S}\beta_{ri}$.

Table 2 Parts of the acquired knowledge

P_1	P_5	P_6	${}^{N}\beta_{ri}$	${}^{U}\beta_{ri}$	${}^{B}\beta_{ri}$	${}^{L}\beta_{ri}$
13	4	8	1	0	0	0
8	13	5	0	1	0	0
17	7	7	0	0	1	0
3	18	10	0	0	0	1
…	…	…	…	…	…	…

We used which data measured in each state had not been learned by the PNN in order to verify the diagnostic capability of the PNN. When inputting the test data, the learned PNN can correctly and quickly diagnose those faults with the possibility grades of the corresponding states.

Some cases of the diagnosis results are shown in Table 3. For example, when we input the test data measured in the normal state into the learned PNN, the possibility grades in the normal state, the unbalance state, the bearing housing looseness state and the belt looseness state, are 95%, 1%, 2%, and 1% respectively. The maximum possibility is 95% for the normal state, so the condition of the blower system should be judged to be in the normal state, which is indicated by *N*. Obviously, the output of the neural network shows correct judgments, and we can obtain the same conclusion by using the data in other states.

Table 3 Examples of verification results

P_1	P_5	P_6	${}^{N}\beta_{ri}$	${}^{U}\beta_{ri}$	${}^{B}\beta_{ri}$	${}^{L}\beta_{ri}$	Judge
16	3	7	0.95	0.01	0.02	0.01	*N*
7	13	3	0.00	0.98	0.01	0.01	*U*
15	7	12	0.07	0.00	0.92	0.01	*B*
5	14	11	0.01	0.02	0.00	0.97	*L*
…	…	…	…	…	…	…	…

* *N*, *U*, *B* and *L* are the normal state, the unbalance state, the bearing housing looseness state, and the belt looseness state, respectively.

According to the verification results, the possibilities outputted by the PNN show the correct judgments in each state. Therefore, the PNN can precisely distinguish the types of the faults on the basis of the possibility distributions of symptom parameters. These results verify the efficiency of the method for diagnosing blower system faults.

7 Conclusion

In order to solve the ambiguous problem between the symptoms and the faults, and effectively diagnose faults for plant machinery, this paper proposed a diagnosis method to distinguish fault types for a blower system based on the rough sets and the fuzzy neural network. The diagnosis knowledge used for the neural network learning can be acquired by the rough sets, and the neural network realized by PNN having learned the diagnosis knowledge can represent complex relationships between symptoms and fault types that are difficult to establish with traditional physical methods. The PNN can quickly converge when learning, and can quickly and automatically distinguish fault types with high accuracy on the basis of the symptom parameters probability distributions when diagnosing. The non-dimensional symptom parameters were also described in the frequency domain; these parameters can reflect the features of the signals measured for the condition diagnosis of plant machinery. This method is suitable for various rotating machines, and had been successfully applied to the condition diagnosis of a blower system.

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