# Fault Diagnosis of Centrifugal Pump Using Symptom Parameters in Frequency Domain

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## ABSTRACT

This paper presents a fault diagnosis method for a centrifugal pump system with frequency-domain symptom parameters by using the wavelet transform, rough sets and a fuzzy neural network to detect faults and distinguish fault types at an early stage. The wavelet transform is used for feature extraction across an optimum frequency region. The diagnosis knowledge for the training of neural network can be acquired by rough sets. A fuzzy neural network called "partially-linearized neural network" is proposed, by which the fault types of machinery can be quickly and effectively distinguished on the basis of the possibility grades of symptom parameters. The non-dimensional symptom parameters that can reflect the characteristics of signals are also described in frequency-domain. Practical examples of diagnosis for a centrifugal pump system are shown to verify the efficiency of the method.

**Keywords:** Fault diagnosis, symptom parameter, frequency domain, neural network, rough sets, centrifugal pump, Japan

## 1. INTRODUCTION

The condition diagnosis technology of plant machinery is very important for guaranteed production efficiency and safety of a machine (Lin Jing and Qu Liangsheng, 2000; B. S. Blackmore *et al*., 2004). Condition diagnosis depends largely on the feature analysis of vibration signals measured for condition diagnosis, so it is important that the feature of the signal should be sensitively extracted when fault occurs at the state change of a machine. However, the feature extraction for the fault diagnosis is difficult since the vibration signals measured at a point of the machine often contains strong noise. Stronger noise than the actual failure signal may lead to misrecognition of the useful information for diagnosis. Therefore, it is important that the noise be canceled from the measured signal as far as possible for sensitively identifying the failure type (Liu and Ling, 1999; Matuyama, 1991; Zhu QB. 2006). Furthermore, in the case of condition diagnosis of pump machinery, the knowledge for distinguishing failures is ambiguous because definite relationships between symptoms and fault types cannot be easily identified. The main reasons can be explained as follows. (1) It is difficult to identify the symptom parameters for diagnosis by which all fault types can be distinguished perfectly. (2) In the early stages of a fault, effects of noise are so strong that the symptoms of a fault are not evident.

The Neural Network (NN) has been used for automated detection and diagnosis of machine conditions (Samanta and Al-Balushi, 2003; M. Diamantopoulou, 2006; R. Q. *et al*., 2006; V. Schetinin and J. Schult. 2006; Su H. and Chong KT. 2007), but the conventional neural network cannot 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 (Bishop, 1995).

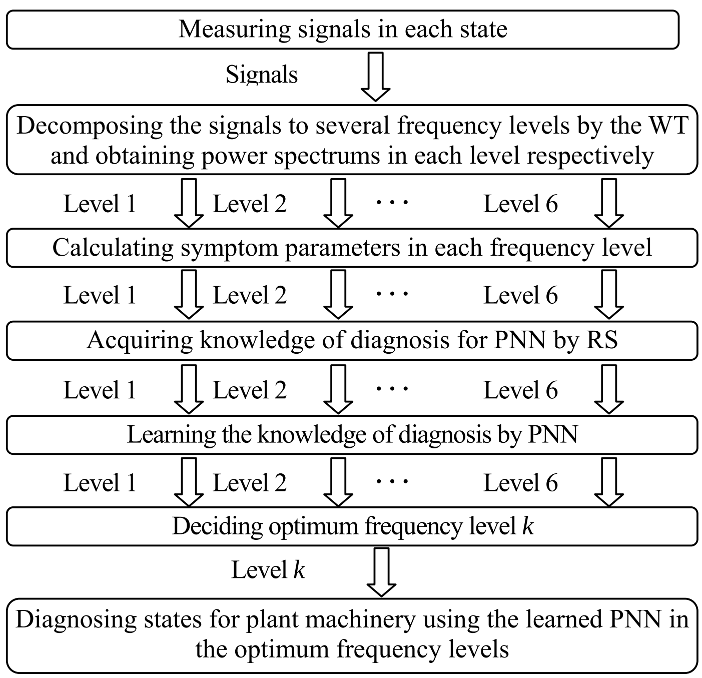


Figure 1. Flowchart of intelligent diagnosis method

For the above reasons, we propose an intelligent diagnosis method for a pump system using the WT, RS and PNN with frequency domain features to detect faults and distinguish fault types at an early stage. The flowchart in Figure 1 shows the method of intelligent diagnosis. The WT performs noise cancellation for feature extraction of the vibration signal across an optimum frequency region. The diagnostic details for the training of the PNN are acquired by the RS (Pawlak, 1982). The fault types of machinery can be automatically distinguished on the basis of the possibility grades of symptom parameters by the PNN. Practical examples of fault diagnosis of a pump system will verify the efficiency of the method.

## 2. CENTRIFUGAL PUMP SYSTEM FOR CONDITION DIAGNOSIS

The centrifugal pump system for condition diagnosis is shown in Figure 2. The motor is employed to drive the pump through a coupling, and the rotation speed can be varied through a speed controller. The flow rate of pump can be also adjusted by the valve control system. Six accelerometers are used to measure vibration signals for fault detection. The sensor locations are shown in Figure 3. Two sensors are put at the pump inlet; two sensors at the pump outlet and other two sensors are placed at the motor and the pump housing respectively. The sampling frequency of the vibration signals for the measurement is 50 kHz, and the sampling time is 10s. The vibration signals are measured at a constant rotation speed of 3500rpm and a constant water flow rate of $19m^3h^{-1}$. In this work, we divided the signal into 100 signal parts, and the sampling number of per signal part is 5000 (the sampling time is 0.1s (5.83 shaft rotations)).

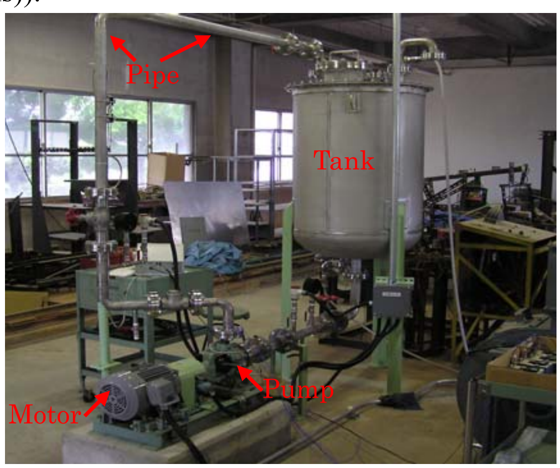


Figure 2. The experiment system of centrifugal pump in the field

Cavitations phenomenon is one of the sources of instability in a centrifugal pump. Cavitations within a centrifugal pump can cause more undesirable effects, such as deterioration of the hydraulic performance, damage of the pump by pitting and erosion and structure vibration and resulting noise (Cudina, 2003). Other faults to be discriminated that often occur in pump systems are shaft misalignment between the motor and the pump, and impeller damage. These faults can cause serious machine accidents and bring great production losses. Diagnosis results of these states will be discussed in a later section. Original vibration signals measured in each state are shown in Figure 4.


Figure 3. The location of the sensors

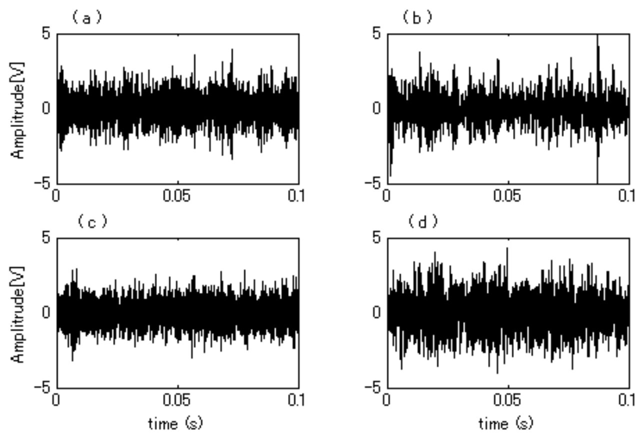


Figure 4. Original signals measured in each state: (a) Normal state, (b) Cavitation state, (c) Impeller damage state, (d) Misalignment state

## 3. FEATURE EXTRACTION USING WT

Wavelet transform is a method of signal analysis in time-frequency domain. It has the local characteristic of time-domain as well as frequency domain. In the field of machinery diagnosis, wavelet analysis has been used in rolling bearing, gearbox and compressor diagnosis and detail mathematical description of WT has been previously formulated (Daubechie, 1990; Prabhakar *et al*., 2002). A brief mathematical summary of WT is provided in this section in relation to the proposed method.

The continuous wavelet transform (CWT) of $f(t)$ is a time-scale method of signal processing that can be defined as the sum over all time of the signal multiplied by scaled, shifted versions of the wavelet function $\psi(t)$. Mathematically,

$$\text{CWT (a,b)} = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} f(t)\psi(\frac{t-b}{a})dt, \quad (a, b \in R) \tag{1}$$

where, $\psi(t)$ denotes the mother wavelet. The parameter $a$ represents the scale factor that is a reciprocal of frequency. The parameter $b$ indicates the time shifting factor. An efficient way to implement this scheme using filters was developed by Mallat (Mallat, 1989).

Using wavelet function a signal can be decomposed into many low frequency [approximations (A)] and high frequency [details (D)] signals. The decomposition process can be iterated, with successive approximations being decomposed in turn, so that a signal can be decomposed into many lower-resolution components. By using reconstruction function, the signal constituents at each level of the decomposition can be reconstructed in time-domain.

In order to extract feature signals in an optimum frequency area, we used the Daubechies (db9) wavelet function (shown in Figure 5) to decompose the signals into six levels in approximations in this work. The Frequency region of each level is shown in Table 1. As an example, the recomposed time signals of each state in level 2 are shown in Figure 6 respectively.

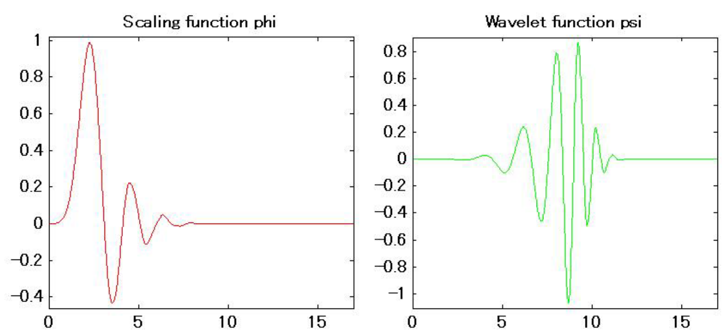


Figure 5. Daubechies (db9) wavelet function

Table 1. Frequency region of each level

| Original signal | 0~50 kHz |
|---|---|
| Approximations (A) | Range of frequency |
| Level $A_1$ | 0~25 kHz |
| Level $A_2$ | 0~12.5 kHz |
| Level $A_3$ | 0~6.25 kHz |
| Level $A_4$ | 0~3.125 kHz |
| Level $A_5$ | 0~1.5625 kHz |
| Level $A_6$ | 0~781.25Hz |

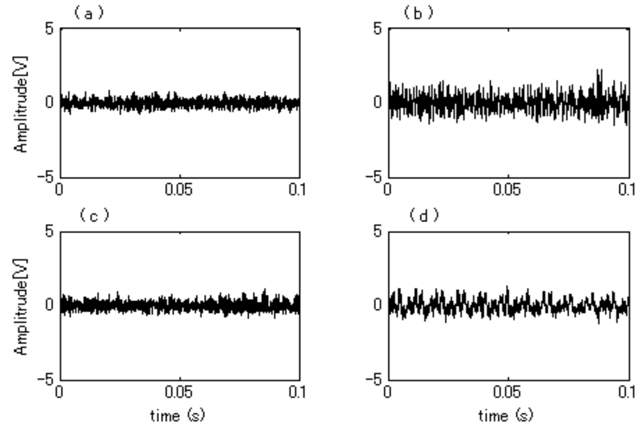


Figure 6. Recomposed signals in level 2 of each state: (a) Normal state, (b) Cavitation state, (c) Impeller damage state, (d) Misalignment state

## 4. SYMPTOM PARAMETERS FOR CONDITION DIAGNOSIS

For automatic diagnosis, symptom parameters by which the fault types can be sensitively distinguished are required. A large set of symptom parameters have been defined in the pattern recognition field (Fukunaga, 1972). Here, seven of these parameters in frequency-domain, commonly used for the fault diagnosis of plant machinery, are considered.

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

$$p_2 = \sqrt{\frac{\sum_{i=1}^{N} f_i^4 \cdot S(f_i)}{\sum_{i=1}^{N} f_i^2 \cdot S(f_i)}} \qquad (3)$$

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

$$p_4 = \frac{\sigma}{\overline{f}} \qquad (5)$$

$$p_5 = \frac{\sum_{i=1}^{N} (f_i - \overline{f})^3 \cdot S(f_i)}{\sigma^3 \cdot N} \qquad (6)$$

$$p_6 = \frac{\sum_{i=1}^{N} (f_i - \overline{f})^4 \cdot S(f_i)}{\sigma^4 \cdot N} \tag{7}$$

$$p_7 = \frac{\sum_{i=1}^{N} \sqrt{\left| f_i - \overline{f} \right|} \cdot S(f_i)}{\sqrt{\sigma} \cdot N} \tag{8}$$

where, $N$ is the number of spectrum line, $f_i$ is the frequency, $S(f_i)$.is the power of spectrum, $\sigma = \sqrt{\frac{\sum_{i=1}^{N} (f_i - \overline{f})^2 \cdot S(f_i)}{N-1}}$ and $\overline{f} = \frac{\sum_{i=1}^{N} f_i \cdot S(f_i)}{\sum_{i=1}^{N} S(f_i)}$.

## 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 (R.S.Milton *et al*., 2004; Pawlak, 1982).

To diagnose states accurately, decrease the number of NN parameter inputs, and increase the efficiency of NN 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 Eq. (2)-(8). Here, $j=1$ *to* $J$, *and* $J$ is the total number of measurement 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.

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

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

$$p = \left\{ p_1, p_2, \cdots, p_m \right\} \tag{10}$$

is the initial symptom parameter set (mentioned in part 4). ${}^j P_S$ is the set of the symptom parameter values measured in the state *S*.

$${}^j p_S = \left\{ {}^j p_{1S}, {}^j p_{2S}, \cdots, {}^j p_{mS} \right\} \tag{11}$$

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

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

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

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

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

(a) Removing $p_i$ from $P$;

(b) Calculating $P_{ij}$ shown in Eq. (13);

(c) If $P_{ij} \neq \Phi$ (empty set), then $p_i$ is the redundant symptom parameter. Removing $p_i$ from $P$. Returning to (a) and repeating from (a) to (c) and from $i$=1 to $i$ =$Q$;

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

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

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

$$^S\beta_{ri} = \frac{card(^S y_j)}{card(y_j)}\% \quad (15)$$

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

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

The input data：The value sets $^{ri}p'$ of the symptom parameters of $r_i$, from which redundant symptom parameters have been removed.

The teacher data: The possibility $^S\beta_{ri}$ of state $S$.

## 6. PARTIALLY-LINEARIZED NEURAL NETWORK (PNN)

The complex relationship between faults and symptoms is difficult to establish the model of condition diagnosis with traditional analysis method. PNN can learn the knowledge acquired by the RS, and the learned PNN automatically distinguishes each state when the value of symptom parameters was inputted. A back propagation (BP) neural network is only used for training the data, and the PNN is used for testing the learned NN.

Here, we describe the principle of the PNN for the fault diagnosis. The neuron numbers of $m$-th layer of a NN is $N_m$. The set $X^{(1)} = \{X_i^{(1,j)}\}$ expresses the pattern inputted to the 1st layer and the set $X^{(M)} = \{X_i^{(M,k)}\}$ is the trainer data to the last layer ($M$-th layer). Here, $i = 1 \ to \ P$, $j = 1 \ to \ N_1$, $k = 1 \ to \ N_M$, and,

$X_i^{(1,j)}$: The value inputted to the $j$-th neuron in the input (1st) layer;

$X_i^{(M,k)}$: The output value of $k$-th neuron in the output ($M$-th) layer; $k = 1 \ to \ N_M$.

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 Figure 7 as "Partially-linearized Neural Network (PNN)".

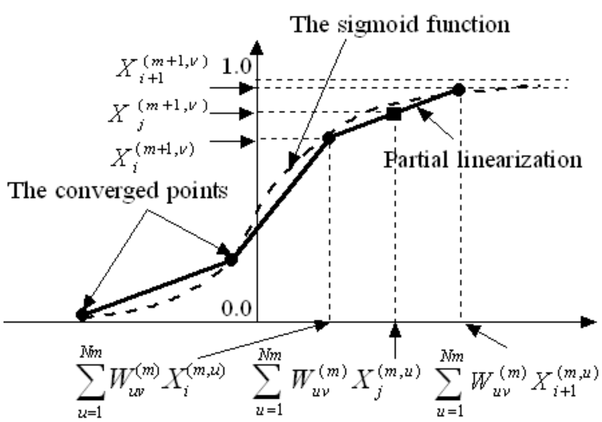


Figure 7. The partial linearization of the sigmoid function

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

$X_i^{(m,t)}$: The value of $t$-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

$$X_j^{(m+1,v)} = X_{i+1}^{(m+1,v)} - \frac{\{\sum_{u=1}^{Nm} W_{uv}^{(m)}(X_{i+1}^{(m,u)} - X_j^{(m,u)})\}(X_{i+1}^{(m+1,v)} - X_i^{(m+1,v)})}{\sum_{u=1}^{Nm} W_{uv}^{(m)}(X_{i+1}^{(m,u)} - X_i^{(m,u)})} \quad (22)$$

By using the operation above, the sigmoid function is partially linearized, as shown in Figure 7. If a function must be learned, the PNN will learn the points indicated by the symbols (●) shown in Figure 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

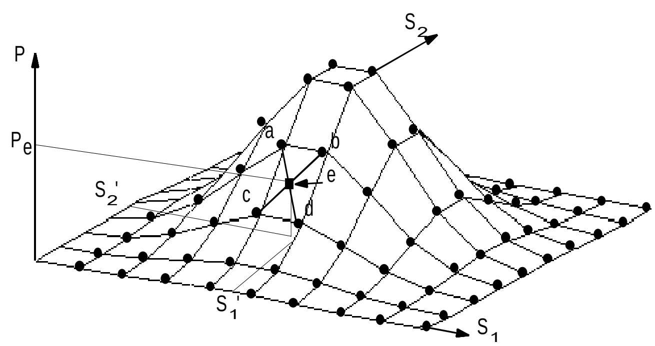


Figure 8. Interpolation by the PNN

## 7. DIAGNOSIS AND VERIFICATION

Vibration signals measured in each state are processed by the Daubechies wavelet function. The original vibration signals are decomposed into six levels in low frequency. The symptom parameters of the recomposed signals are calculated in frequency domain by Eq. (2)-(8). They are digitized as the training data for the PNN by Eq. (9). The redundant symptom parameters removed by the algorithm shown from step (a) to (d) in chapter 5. Table 2 shows the redundant symptom parameters in each level marked with "×". For example, we can distinguish each sated by only using $p_2$, $p_5$ and $p_7$ in level $A_1$.

A back propagation (BP) neural network is only used for training the data, and the PNN is used for testing the learned NN. Figure 9 shows the PNN built on the basis of method proposed in this paper, it consists of the first layer, the hidden layers and the last layer. The neurons in the first layer are inputted the symptom parameters processed by the rough sets. The number of neurons in the hidden layer is eighty. The outputs in the last layer are ${}^{N}\beta_{ri}$, ${}^{C}\beta_{ri}$, ${}^{M}\beta_{ri}$, and ${}^{D}\beta_{ri}$ which are the possibility grades of normal state, cavitation state, misalignment state and impeller damage respectively.

Table 2. Redundant symptom parameters in each level

| Symptom Parameters | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_5$ | $P_6$ | $P_7$ |
|---|---|---|---|---|---|---|---|
| Original | × | × | O | × | O | × | O |
| Level $A_1$ | × | O | × | × | O | × | O |
| Level $A_2$ | × | O | × | × | O | O | O |
| Level $A_3$ | × | × | × | O | O | × | × |
| Level $A_4$ | × | × | × | O | O | O | × |
| Level $A_5$ | O | × | × | × | × | O | O |
| Level $A_6$ | × | × | × | × | O | O | O |

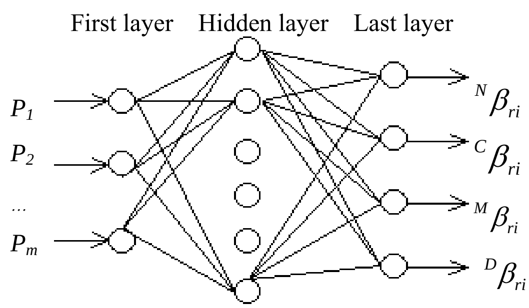


Figure 9. Paritially-linearized neural network

Table 3. Examples of training data for the PNN learning

(a) Data using original signals

| $P_3$ | $P_5$ | $P_7$ | ${}^N\beta_{ri}$ | ${}^C\beta_{ri}$ | ${}^M\beta_{ri}$ | ${}^D\beta_{ri}$ |
|---|---|---|---|---|---|---|
| 13 | 19 | 2 | 1 | 0 | 0 | 0 |
| 3 | 12 | 13 | 0 | 1 | 0 | 0 |
| 19 | 2 | 13 | 0 | 0 | 1 | 0 |
| … | … | … | … | … | … | … |

(b) Data using the recomposed signals in level $A_1$

| $P_2$ | $P_5$ | $P_7$ | ${}^N\beta_{ri}$ | ${}^C\beta_{ri}$ | ${}^M\beta_{ri}$ | ${}^D\beta_{ri}$ |
|---|---|---|---|---|---|---|
| 6 | 1 | 4 | 1 | 0 | 0 | 0 |
| 1 | 19 | 18 | 0 | 1 | 0 | 0 |
| 19 | 9 | 1 | 0 | 0 | 1 | 0 |
| … | … | … | … | … | … | … |

The knowledge of diagnosis for PNN learning can be acquired by the RS in each level. Parts of the training data are shown in Table 3. The PNN are quickly convergent by learning the training data. 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 ${}^{S}\beta_{ri}$. Figure 10 shows a comparison between original signals and the decomposed signals for detection rate in each state; the detection rates are different for different levels.

According to the verification results by the PNN using the original signal (in level $A_o$), the probabilities of correct judgment in normal state, cavitation state, misalignment state and impeller damage state are 95%, 79%, 98.8%, and 89% respectively. The different features of the states have appeared in different frequency levels, so we used the recomposed signals and obtained the highest detection rate of 99% at level $A_6$ for distinguishing the normal state from abnormal states; the highest detection rate of 99% at level $A_6$ for distinguishing the misalignment state from other states; the higher detection rate (more than 98%) at level $A_2$, $A_3$ or $A_5$ for distinguishing the cavitation state from other states; the higher detection rate of 98.8% at level $A_o$ and $A_4$ for distinguishing the impeller damage state from other states. Those results verified the efficiency of the intelligent diagnosis method for diagnosing pump system faults.

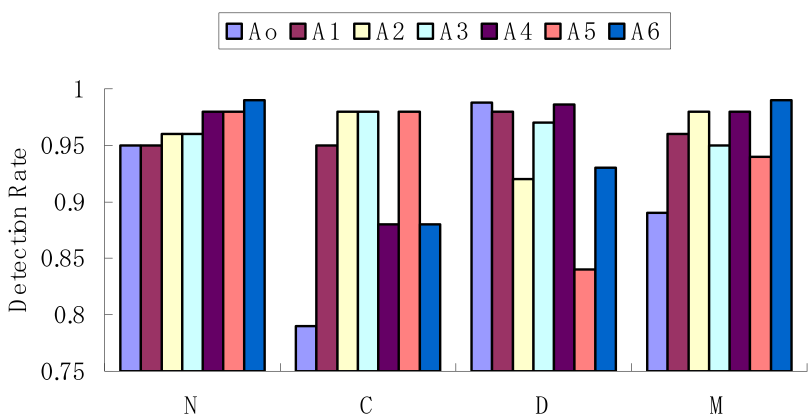


Figure 10. Detection rates in each state. N: Normal state, C: Cavitation state, D: Impeller damage state, M: Misalignment state.

## 8. CONCLUSION

Machinery diagnosis depends largely on the feature extraction of machinery signals, so it is important that the extracted features should be both sensitive to fault occurrence and reliable against disturbances. In order to effectively diagnose faults, this paper proposes an intelligent diagnosis method with the symptom parameters in frequency domain based on the wavelet transform (WT), the rough sets (RS) and the partially-linearized neural network (PNN). The wavelet transform is used for feature extraction across an optimum frequency region. The diagnosis knowledge for the training of the PNN can be acquired by using the RS. The PNN, having acquired the diagnosis knowledge, can represent complex relationships between symptoms and fault types that are difficult to model with traditional physical methods. 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 symptom parameters when diagnosing. The decision method of optimum frequency area for the feature extraction of the signals is also discussed using real plant data. The non-dimensional symptom parameters are also described in frequency domain, and these parameters can reflect the characteristics of the signals measured for the condition diagnosis of the pump. This method is suitable for different rotating machinery, and has been successfully applied to the condition diagnosis of a centrifugal pump system.

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