Fault diagnostic system for rotating machine based on Wavelet packet transform and Elman neural network

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Abstract

An efficient fault diagnosis system is needed for industry because it can optimize the resources management and improve the performance of the system. In this study, a fault diagnostic system is proposed for rotating machine using wavelet packet transform (WPT) and elman neural network (ENN) techniques. In most fault diagnosis for mechanical systems, WPT is a well-known signal processing technique for fault detection and identification. In previous work, WPT can improve the continuous wavelet transform (CWT) used over a longer computing time and huge operand. It can also solve the frequency-band disagreement by discrete wavelet transform (DWT) only breaking up the approximation version. In the experimental work, the extracted features from the WPT are used as inputs in an Elman neural network. The results show that the scheme can reliably diagnose four different conditions and can be considered as an improvement of previous works in this field.

Key Words : fault diagnosis system, wavelet packet transform, Elman neural network

1. Introduction

Fault Diagnosis in rotating parts is required to prevent serious damage to mechanical systems. In general, the conditions of rotating machines can be monitored by measuring the mechanical vibration signal. Generally, there is a corresponding fundamental frequency in each moving part of a machine. If a fault occurs in a moving part, the vibration amplitudes of the corresponding fundamental frequency and the harmonic frequencies rise. In conventional fault diagnosis techniques, the amplitude difference in the frequency domain which can be obtained by Fast Fourier Transform (FFT) technique is used to detect or diagnose the fault. However, since the faults in practice are various and non-stationary, the analysis in terms of their spectrum is inadequate, and it is difficult to classify the faults in detail. Several studies show that the fault in a moving part affects the distribution and amplitude of the spectrum of the vibration signal, which leads to the redistribution of energy of the signal in each frequency band [1-2]. Recently, Wavelet analysis has become a useful tool for fault diagnosis of a mechanical system. In 1997, Li and Ma proposed a new approach for bearing-localized defect detection based on wavelet transform [3]. In 2000, Sung et al. developed an approach to analyze the location defect based on discrete wavelet transform [4]. In 2002, Zheng et al. proposed a concept of time average wavelet spectrum based on continuous wavelet transform (CWT) [5].

Whereas the wavelet transform decomposes only the low frequency components, wavelet packet transform (WPT) de-

composes the signal utilizing both the low-frequency components and the high frequency components. This flexibility of a rich collection of abundant information with arbitrary time-frequency resolution allows extraction of features that combine non-stationary and stationary characteristics. In the fault diagnosis field, extracting fault features plays an important role. After extracting the fault features, an artificial neural network is indispensable for aiding the fault classification. An intelligent fault diagnosis is performed throughout combining the fault diagnosis system with an artificial neural network.

In this work, a new type of fault diagnostic algorithm based on wavelet packet tree for frequency ordering and ENN is proposed. Fault feature data are extracted from the wavelet packet tree calculated for frequency ordering. Furthermore, these feature data are used for training ENN. To verify the performance of the proposed diagnostic algorithm, several simulation studies are carried out.

2. Background knowledge

2.1 Wavelet packet transformation

Wavelet analysis is mathematical theory and a method newly developed in the last ten years. It has a feature of multi-resolution analysis. Generally, wavelet transform provides one with more flexible time-frequency resolution properties.

We introduce an analyzing function $\psi(t)$ commonly referred to the mother wavelet and if $\psi(t)$ meets with $\int_R \psi(t) dt = 0$, then $\psi(t)$ is called basis wavelet. According to Mallat Algorithm, a time series signal $\{x(n \triangle t) | n = 1, 2, \dots, N\}$ in space $L^2(R)$, there exists the following discrete wavelet decomposition:

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$$x_k^{(j+1)} = \sum_n h(n-2k)x_n^{(j)}, d_k^{(j+1)} = \sum_n g(n-2k)d_n^{(j)} \quad (1)$$

where $x_k^{(j)}$ are approximation coefficients of $x(n \triangle t)$ under scale j , $d_k^{(j)}$ are detailed coefficients of $x(n \triangle t)$ under scale j , and $h(k)$ and $g(k)$ are low pass filter coefficients and high pass filter coefficients, respectively. Detailed coefficients $d_k^{(j)}$ and approximation coefficients $x_k^{(j)}$ can reconstruct $x_k^{(j-1)}$, their relationship are:

$$x_k^{(j-1)} = \sum_n h(k-2n)x_n^{(j)} + \sum_n g(k-2n)d_n^{(j)} \quad (2)$$

The larger the coefficients obtained by wavelet decomposition, the signal have more energy carried in the information, and vice-versa. However, one drawback of wavelet transform is that the frequency resolution is rather poor in the high-frequency region. Therefore, it faces some difficulties for discrimination between signals having high-frequency components.

Fig. 1 Conventional wavelet packet decomposition

Wavelet packet decomposition, which has finer analytic results, is the extension of wavelet decomposition. In the standard wavelet packet transform, the result of the scaling function (the low pass filter) is placed in the lower half of the array and the result of the wavelet function (the high pass filter) is placed in the upper half of the array as shown in Fig.1. The wavelet packet algorithm recursively applies the wavelet transform to the high and low pass result at each level, generating two new filter results which have half the number of elements.

However, the result of the wavelet packet transform is not ordered by increasing frequency. If the lower and upper halves of the array that results from the conventional wavelet packet decomposition are considered as two children in the wavelet packet tree, children in ordered wavelet packet tree are bordered by inverting the location of the filter result in the right hand child [9]. The procedure for the generation of children in ordered wavelet packet tree is shown in Fig.2. In this diagram, the low pass filter is represented as H and the high pass filter is shown as G.

Fig. 2 Frequency ordered wavelet packet tree

For the frequency ordered wavelet packet tree in Fig.2, if the maximum frequency is f , the first array (S_0^0) will contain the frequency range $\{0..(f/8)-1\}$, the second array (S_1^1) will contain frequencies $\{f/8..(f/4)-1\}$, the third array contain frequencies $\{f/4..(3f/8)-1\}$ and the last array (S_3^7) will contain frequencies $\{7f/8..f\}$. By focusing on this property of frequency ordered packet tree, the time/frequency resolution matrix can be obtained by taking each array as a row element of matrix. That is, each array from left to right are stacked to form a matrix, where x-axis is time and y-axis is frequency. In case of Fig.2, wavelet time/frequency resolution matrix can be obtained as in Fig.3.

Fig. 3 Wavelet time/frequency resolution matrix

2.2 Feature extraction using wavelet time/frequency resolution matrix

For the better understanding of extraction of feature data from time/frequency resolution matrix, we consider the non-stationary signal shown in Fig.4.

If we apply wavelet time/frequency resolution technique to the signal shown in Fig.4, time/frequency matrix can be graphically depicted in Fig.5.

With the help of graphical view of wavelet time/frequency resolution matrix, time variation of frequency components on the time axis can be easily observed. As can be seen in Fig.5, dominant frequency changes from low frequency band to high frequency band as time goes by.

Fig. 4 Non-stationary signal

Fig. 5 Graphical representation of wavelet time/frequency resolution matrix

By utilizing this property, some valuable feature vectors can be generated from time/frequency resolution matrix. The steps for extracting the feature information are as follows.

(1) Choose a suitable wavelet basis to make j -layer wavelet-packet decomposition, and then mapping the signal to m ($m=2^j$) independent frequency bands.

(2) As in Fig.1 and Fig.2, S_3^0 presents the symbol for a subspace that stands for the third resolution and the 0-th subspace. Let's define S_j^n is a symbol for the j -th resolution and the n -th subspace, and $S_j^n(k)$ is the coefficient of the subspace after wavelet packet decomposition, $n=0, \dots, 2^j-1$.

Let's assume that there are p data points in original signal. After taking j -level wavelet packet decomposition, there are 2^j subspaces in the wavelet packet tree. The dimension of each subspace is $p/2^j$.

We can calculate the mean value of coefficients of all the subspaces as follows.

$$E_k = \frac{1}{2^j} \sum_{n=0}^{2^j-1} S_j^n(k) \quad k=1, \dots, n/2^j \quad (3)$$

(3) Form a feature vector. By using the mean value, following feature vector can be obtained.

$$E = [E_1, E_2, \dots, E_k] \quad (4)$$

Feature vector expressed in eq.(4) can be thought of as a sequential pattern to be used for training the neural network classifier.

2.3 Fault diagnostic algorithm based on ENN

After extracting fault features, a proper artificial neural network is indispensable for aiding the fault classification. An Intelligent fault diagnostic system is performed by combining the fault diagnostic approach with an artificial neural network. In this work, ENN [10] which was invented by Jeff Elman was introduced. ENN is two-layer back propagation network, with the addition of a feedback connection from the output of the hidden layer to its input. This connection is called the context nodes. Both the input units and context nodes activate the hidden nodes; and then the hidden nodes feed forward to activate the output nodes. The hidden nodes also feed back to activate the context nodes. The architecture of ENN is shown in Fig.6. The dynamics of the ENN are described by the following equation:

$$X_h(k+1) = S\{W_c X_c(k+1) + W_i U(k)\} \quad (5)$$

$$X_c(k+1) = W_r X_h \quad (6)$$

$$Y(k+1) = W_o X_h(k+1) \quad (7)$$

Where S is a hyperbolic tangent function; $U(k)$ and $Y(k)$ are the input and the output of the network at a discrete time k ; X_c and X_h are the output of context neurons and the neurons in hidden layers; W_c , W_i , W_r and W_o are the weight matrices for the context-hidden, input-hidden, hidden-context and hidden-output layer, respectively. Training of the ENN is performed by the faster back-propagation (BP) algorithm.

Fig. 6 Structure of ENN

Elman network differs from conventional ones in that the input layer has a recurrent connection with the hidden units. Therefore, at each time step, the output values of the hidden units are copied to the input units, which store them and use them for the next time step. This architecture allows the network to memorize information from the past,

in such a way to better detect periodicity of the patterns. If different fault occurs, its corresponding different sequential pattern expressed in Eq. (4) can be generated. Therefore, this sequential pattern corresponding to each fault is stored in ENN, in which efficient fault classification can be carried out. The proposed fault diagnostic algorithm based on ENN is shown in Fig.7.

Fig. 7 Flow chart of the proposed fault diagnostic algorithm

3. Experimental investigation of faults identification

3.1 Performance test of the proposed scheme to real fault signal

Three types of faults are considered to verify the performance of the proposed fault diagnostic scheme. The induction motor drive system used in this experiment is shown in Fig.8 and operated in 1690 rpm. Four conditions are tested, including the rotating machines without any fault, with a loose base bolt, with a bearing housing fault and with a unbalanced load.

Fig. 8 Experimental system for the test

The test system is composed of a speed control unit, three-phase induction motor, a 3-axis accelerometer (Freescale Semiconductor's MMA 7260Q), data acquisition board connected with notebook PC via PCMCIA (Personal

Computer Memory Card International Association) and Matlab program for fault diagnosis. The accelerometer is placed on the surface of the motor housing for measuring vibration and its signal is sampled at a frequency of 1KHz. Four types of vibration signals corresponding to each condition are shown in Fig. 9 to Fig.12.

Fig. 9 Vibration signal from the rotating machine in normal operation

Fig. 10 Vibration signal from the rotating machine with a loose base bolt

Fig. 11 Vibration signal from the rotating machine with a unbalanced load

Fig. 12 Vibration signal from the rotating machine with a bearing housing fault

In the study, frequency ordered wavelet packet transform is utilized for the feature extraction from the vibration signal. Each sequential pattern obtained from eqsf(4) corresponding to each et pacrom hown in Fig.13 to Fig.16.

Fig. 13 Sequential pattern for normal operation (a) and its various sequential patterns obtained by shifting window (b)

Fig. 14 Sequential pattern for rotating machine with a loose base bolt (a) and its various sequential patterns obtained by shifting window (b)

Fig. 15 Sequential pattern for the rotating machine with an unbalanced load (a) and its various sequential patterns obtained by shifting window (b)

Fig. 16 Sequential pattern for the rotating machine with a bearing housing fault (a) and its various sequential patterns obtained by shifting window (b)

In each figure, a sequential pattern depicted in each figures as (a) can be obtained by applying WPT algorithm to vibration signal shown in Fig.9 to Fig.12 and they are used for training data for ENN. If the ENN has been successfully trained with these data, each sequential patterns were memorized into the ENN. For the performance test of the trained ENN, some sequential patterns corresponding each fault are required. For obtaining various sequential patterns corresponding to each fault, some part of vibration signal are taken by shifting window sized of 500 data points. The obtained various sequential patterns for each fault are shown in (b).

As you can see the figures, various sequential patterns obtained by shifting window can be thought of as a subset of their original sequential pattern.

For the efficient training of ENN and fault diagnosis, Neural Network Toolbox and Simulink of Matlab are used.

The number of neurons in input of ENN is one and the number of output neurons is two. On the other hand, number of neurons in hidden layer is 300. The corresponding target values used for training ENN is $[0,0]$, $[0,1]$, $[1,0]$, $[1,1]$, respectively. Output $O=[0,0]$ means normal condition of the rotating machine and output $O=[0,1]$ means a fault related with loose base bolt. Similarly, output $O=[1,0]$ means an unbalance load and output $O=[1,1]$ means a bearing housing fault. In order to verify the performance of the trained ENN, three groups of fault signals are provided. The diagnostic result of the proposed scheme is shown in Fig.17.

There are four groups of sequential patterns for each fault. Each group has three sequential patterns obtained by

moving window and these are used to test the trained neural network.

During the time step from 0 to 18, the first group of sequential patterns which represent the normal condition are input to the trained ENN. The desired output should be $[0,0]$. During the time step from 19 to 36, the second group of sequential patterns which represent the loose base bolt fault are input to the trained ENN. The target output should be $[0,1]$. During the time step from 37 to 54, the third group of sequential patterns which represent the machine with an unbalance load are input to the trained ENN. The target output should be $[1,0]$. During the time step from 55 to 72, the forth group of sequential patterns which represent the machine with a bearing housing fault are input to the trained ENN. The target output should be $[1,1]$.

As can be seen in Fig17, the test results are very good. The test outputs are almost the same as the target output.

Fig. 17 Diagnostic result

4. Conclusion

In this work, a fault diagnosis system based on both frequency ordered WPT for feature extraction and classification using ENN was proposed. Furthermore, fault feature extraction scheme based on time/frequency resolution matrix which can be obtained using frequency ordered WPT was also proposed. Experimental result showed that the vibration signal coming from the rotating machine can be effectively used to diagnose the condition of the rotating

machines. Unfortunately, stationary fault signals were considered in this work owing to the difficulty in getting hold of non-stationary fault signals. However, considering that WPT can be effectively applied to non-stationary signals, the proposed fault diagnostic scheme can be utilized for complex fault signal that shows non-stationary property.

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