Air compressor fault diagnosis based on lifting wavelet transform and probabilistic neural network

W S Yang¹², Y X Su¹ and Y P Chen¹
¹School of Automation, Wuhan University of Technology, Wuhan 430070, China
E-mail: 445926762@qq.com

Abstract. Due to the wide variety of faults, the components of air compressor fault condition vibration signal are complex. Fault features extracted by conventional time-frequency analysis and multi-resolution analysis are not comprehensive enough to reflect the fault condition of air compressor. To overcome this deficiency, this paper proposes an air compressor fault diagnosis algorithm based on lifting wavelet. Firstly, the vibration signal of the air compressor is decomposed by lifting wavelet; then the statistic such as the peak value and Kurtosis of the decomposition layer is calculated as the fault features. Finally, Probabilistic Neural Network is utilized to classify the fault state. In the experiment, the fault extraction methods such as Wavelet Packet Decomposition and Continuous Wavelet Transform are compared. The results indicate that the fault features extracted by lifting wavelet are more comprehensively to reflect the fault condition of air compressor while other fault character extraction methods need more fault characteristics; the fault diagnosis accuracy by utilizing proposed method is high and the training time is short, which is more suitable for the online fault diagnosis of the actual air compressor.

1. Introduction
In the air compressor health management system, fault diagnosis is generally performed by extracting fault characteristics from the air compressor vibration signal [1]. Therefore, the fault feature extraction in the vibration signal is the key to the high efficient fault diagnosis of the air compressor. Due to the wide variety of compressor failures and the rough working conditions, the vibration signal is doped with noise signal, stationary signal and non-stationary signal [2].

Conventional frequency analysis methods such as Discrete Fourier Transform and Fast Fourier transform can extract the signal frequency components and distribution. Since the air compressor fault vibration signal contains non-stationary signal, the fourier analysis has a poor resolution for the non-stationary signal with time-varying frequency, so the fault information extraction is not integrated [3].

The Wavelet Transform uses the wavelet function to convolve the signal based on the Fourier Transform, and can process the abrupt signal as well as the non-stationary signal. The Wavelet Transform essentially performs a series of correlation operations on each transform scale. When the signal characteristics are similar to those of the wavelet function, large wavelet coefficients will appear. Wavelet transform includes Continuous Wavelet Transform, Discrete Wavelet Transform and Wavelet Packet Transform [4]. When using Continuous Wavelet Transform to extract fault features, since many wavelet functions can be selected, and those can be evaluated by different verification criteria. Nishchal [3], Kalyan [4] used Shannon Entropy as the verification standard. In recent years, wavelet transform has been utilized as a popular method in the field of condition monitoring and fault diagnosis. Literature [16-18] utilized wavelet transform to extract air compressor vibration signal information for denoising.
and fault diagnosis.

Since the Continuous Wavelet Transform and the Discrete Wavelet Transform have poor resolution in the high frequency subband, if the mechanical vibration fault signal exists in the higher frequency subband, the use of wavelet transform will result in loss of fault features in some high frequency components. Wavelet Packet Transform can provide more detailed decomposition of high frequency subband, extract more medium and high frequency information signals, with better ability of localized time-frequency analysis [5].

The momentous difference between the Lifting Wavelet Transform and the classical wavelet transform is that the former does not use the Fourier transform, and all the operations are performed in the time domain, but the same time-frequency localization can be obtained [9]. Secondly, regardless of how the predictor and updater are chosen, the wavelet transform can always be fully reconstructed. The wavelet function and the scale function are determined by the predictor and the updater in lifting wavelet scheme. The selection of the predictor and updater is equivalent to the construction of wavelet functions in traditional wavelet analysis. Lifting wavelets have been used in gear and bearing fault diagnosis. Zhou [6] utilized the lifting wavelet to extract the fault features of the gearbox and gasoline engine. Jiao [7] utilized the lifting wavelet to extract the acoustic emission signal in thermal leak diagnosis to determine the leakage frequency. Zhong [8] utilized the lifting wavelet to extract the turbopump fault. Compared with conventional wavelet analysis, for the same length data, the calculation of lifting wavelet is simpler, and in-place calculation is allowed, which consumes less memory and is more suitable for online processing of signals, adaptive and nonlinear transformation [11]. Lifting wavelet scheme has been applied in gear and bearing fault diagnosis [5-10], and less applied in air compressor fault diagnosis. To overcome the deficiency of difficulty in extracting fault features in air compressor fault diagnosis, lifting wavelet analysis combined with Probabilistic Neural Network was introduced to diagnose fault of the air compressor.

2. Lifting wavelet transform scheme

The Lifting Wavelet Transform consists of two processes of decomposition and reconstruction. The decomposition procedure includes three steps of split, prediction and update [9]; the reconstruction procedure is the inverse process of the decomposition.

Let \( s = \{x(k), k \in Z\} \) be the data sequence. The decomposition procedure of the Lifting Wavelet Transform is as follows:

Split: The data sequence \( s = \{x(k), k \in Z\} \) is decomposed into 2 sequences \( x_o(k), x_e(k) \) according to the equations (1) and (2):

\[
x_o(k) = x(2k + 1) \quad k \in Z \tag{1}
\]

\[
x_e(k) = x(2k) \quad k \in Z \tag{2}
\]

Prediction: Using \( x_e(k) \) to predict \( x_o(k) \), the detail signal \( d(k) \) is generated according to equation (3), where \( P(\cdot) \) is a predictor.

\[
d(k) = x_o(k) - P[x_e(k)] \quad k \in Z \tag{3}
\]

Update: The \( x_e(k) \) is updated with the detail signal \( d(k) \), and the approximation signal \( c(k) \) is generated according to the equation (4), where \( U(\cdot) \) is an updater.

\[
c(k) = x_e(k) - U[d(k)] \quad k \in Z \tag{4}
\]

By iterating the above three steps, the detail signal and the approximation signal at different levels can be generated. Lifting wavelet reconstruction procedure is the inverse of the above process, and the reconstruction procedure is as shown in equation (5).

\[
\begin{align*}
x_o(k) &= c(k) - U[d(k)] \quad k \in Z \\
x_e(k) &= d(d) + P[x_e(k)] \quad k \in Z
\end{align*} \tag{5}
\]
From the decomposition of the lifting wavelet algorithm, it can be seen that the sequence is decomposed into a more compact representation, then different predictors and updaters are equivalent to select different filter banks in the wavelet decomposition. The lifting wavelet decomposition procedure are shown in figure 1. In this paper, the Interpolation Subdivision algorithm is used to construct the wavelet scale function and the wavelet function.

The Interpolation Subdivision algorithm constructs the wavelet scaling function as follows:

Step1: The detail coefficient is initialized to a 0 sequence, and the approximation coefficient is initialized to a \( \delta \) sequence;
Step2: Reconstruct the signal by using equation (5);
Step3: Determine whether the wavelet scale function is smooth; if the scale function is not smooth, assign the signal value to the detail coefficient and get to Step2; otherwise the algorithm ends.

The Interpolation Subdivision algorithm constructs the wavelet function method similarly to the construction scale function method.

3. Probabilistic neural network

PNN (Probabilistic Neural Network) is a branch of a radial basis network and belong to a feedforward network, frequently used in classification and pattern recognition problems [13-15].

The theoretical basis of PNN is the Bayesian Minimum Risk Criterion (Bayesian Decision Theory). In the fault diagnosis classification, it can be described as: Let \( CA, CB \) be two types of failure modes. \( NA, NB \) is the number of samples for each failure mode, and \( N \) is the total number of samples. The fault feature samples are \( X = (x_1, x_2, x_3, \ldots, x_n) \). The judgment is made using the equation (6).

\[
\begin{align*}
\text{if } h_A l_A f_A(X) > h_B l_B f_B(X), & \quad \text{then } X \in CA \\
\text{if } h_A l_A f_A(X) < h_B l_B f_B(X), & \quad \text{then } X \in CB
\end{align*}
\]

Where: \( h_A, h_B \) represents the prior probability of failure mode \( CA, CB \), generally taking \( h_A = N_A / N, h_B = N_B / N \);
\( l_A, l_B \) represents the cost factors of the misclassification; \( f_A, f_B \) represents the probability density functions, which can be generated by the Parzen method (7):

\[
f_A = \frac{1}{(2\pi)^{P/2}\delta^P} \sum_{i=1}^{N_A} \exp \left[ -\frac{(X - X_{ai})^T(X - X_{ai})}{2\delta^2} \right]
\]

Where: \( X_{ai} \) represents the \( i \)th training vector of failure mode \( CA \), and \( \delta \) represents the smoothing parameter.

The PNN consists of an input layer, a mode layer, a summation layer and an output layer. The topology diagram is shown in figure 2.
The first layer is the Input layer. The number of Input layer neurons is consistent with the input sample dimension. The second layer is the Pattern layer. Each Mode layer node weights and sums the data transmitted from the Input layer, and passes those data to the Summation layer by Pattern layer through a nonlinear operation. The nonlinear operator uses equation (8):

$$g(z_j) = \exp((z_j - 1)/\delta^2)$$  \hspace{1cm} (8)

The third layer is the Summation layer, and the data from the same type of Mode layer are accumulated to generate an estimated probability density function of the failure mode. The fourth layer is the Output layer, and the Output layer selects a neuron with the largest a posteriori probability density as the output of the entire system. Therefore, the PNN is equivalent to the Bayesian pattern classification method when the multivariate probability density function of the Gaussian kernel is used.

4. Proposed fault diagnosis scheme
The fault diagnosis scheme is divided into 3 steps.

The first step: pre-processing the acquired signal. The data set used in this paper is from [3], where the preprocessing process has been filtered, cropped, smoothed, and normalized. For details, please refer to literature [3].

The second step: fault feature extraction. In this paper, Daubechies-4 (db4) is used to perform 3-layer lifting wavelet decomposition on the pre-processed data. 5 statistics of peak value, mean, standard deviation, skewness and kurtosis are calculated in the third layer as a fault feature.

When the discrete Fourier transform is used, an 8-band signal energy spectrum is obtained as the fault feature.

When using continuous wavelet transform, the Morlet wavelet function is selected, and the signal is decomposed into 7 layers, and 5 statistics (same as lifting wavelet) in the 7th layer signal are taken as fault features.

When using the wavelet packet decomposition, the Daubechies-4 (db4) wavelet basis function is used to decompose the signal into 7 layers, and the energy of each node is calculated by the equation (9):

$$E_i = \sum_{n_i} x[n]^2$$  \hspace{1cm} (9)

In equation (9), $E_i$ is energy at $i^{th}$ node and $n_i$ is the number of instances of $i^{th}$ node. A total of 254 node energies are obtained (excluding the first layer nodes). Therefore, 254 eigenvalues can be obtained by decomposing the signal using the wavelet packet decomposition.

The third step: classification of fault features, this paper uses Probabilistic Neural Networks to classify faults. 5 fault features are generated from lifting wavelet extraction. 8 fault features are
generated from discrete Fourier transform, 5 fault features are generated from continuous wavelet transform, and 254 from wavelet packet transform.

5. Result and conclusion

The experimental data is divided into 8 categories, which include a healthy state, and 7 faulty states: LIV fault (LIV), leakage outlet valve (LOV) fault, non-return valve (NRV) fault, piston ring fault (Piston), flywheel fault (Flywheel), rider belt fault (Riderbelt) and bearing fault. Every category data set includes 225 24 Bit PCM format files at 50 kHz sampling rate.

The diagnosis accuracies is shown in table 1, and the time for training neural network is shown in table 2. Table 1 indicates that the fault diagnosis accuracy using the discrete Fourier analysis is the lowest (all 8 state), and the proposed algorithm has the highest accuracy. Among 8 fault conditions, Piston and Flywheel fault have the lowest accuracy. By utilizing Fast Fourier analysis for those 2 fault conditions, we can analysis their frequency distribution. Figure 3 is the raw signal frequency spectrum of these two faults. Figure 3 indicates that the vibration signals of both Piston and Flywheel faults contain 890 Hz and 2100 Hz frequencies. Therefore, it is difficult to distinguish the two types of faults by using the Discrete Fourier transform. Figure 4 is the 3rd decomposition layer frequency spectrum by using lifting wavelet transform. Figure 4 indicates that the lifting wavelet analysis can more fully extract the original signal fault features.

| Extraction Method | DFT | CWT | WPT | Lift Wavelet |
|-------------------|-----|-----|-----|-------------|
| Healthy           | 86% | 92% | 92% | 94%         |
| LOV               | 86% | 94% | 94% | 96%         |
| LIV               | 74% | 96% | 96% | 97%         |
| Piston            | 32% | 72% | 90% | 89%         |
| Flywheel          | 37% | 80% | 87% | 90%         |
| Bearing           | 77% | 88% | 88% | 84%         |
| NRV               | 75% | 87% | 87% | 90%         |
| Riderbelt         | 71% | 79% | 85% | 92%         |

Table 2. PNN training time.

| Extraction Method | Time (sec) |
|-------------------|------------|
| DFT               | 0.056      |
| CWT               | 0.054      |
| WPT               | 2.101      |
| LiftWavelet       | 0.054      |

In order to further compare the extraction fault features ability between wavelet analysis and the lifting wavelet, the Wavelet Packet in the experiment selects 254 fault features, while the lifting wavelet selects only 5 fault features. From table 1, the fault diagnosis accuracy by using Wavelet Packet decomposition with 254 fault features can be close to the proposed algorithm. However, as can be seen from table 2, due to the large number of fault features, the training time increases accordingly.

Therefore, from the experiment, the proposed algorithm can have a higher fault diagnosis rate when selecting fewer fault features, so it is more suitable for online fault diagnosis.
Figure 3. The raw signal frequency spectrum graph.

Figure 4. The frequency spectrum graph by utilizing Lifting wavelet transform.

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