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Research on fault diagnosis method of piston rod based on harmonic wavelet and manifold learning①

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Abstract

As the core part of reciprocating compressor, piston rod is easy to cause a serious accident when abrasion and breakage fault occur to it. Therefore, it is very important to monitor its running state. At present, a small number of reciprocating compressors have been installed on-line monitoring and diagnosis system, most of which can only monitor a single vertical subsidence of piston rod and it can't fully represent the running state of piston rod. Therefore, a method of monitoring the vertical and horizontal displacement of piston rod axis orbit is simultaneously used. In view of the characteristics that the piston rod axis orbit is disordered and difficult to extract features, purification of the axis orbit is carried out based on harmonic wavelet and then features are extracted such as vibration energy, natural frequency and the axis orbit envelope area. After that, a nonlinear local tangent space manifold learning algorithm is used to reduce the dimension of the features and obtain sensitive features. By analyzing the practical cases, the effectiveness of the method for fault monitoring and diagnosis of reciprocating compressor piston rod assembly has been verified. Finally, as BP neural network has the characteristics of solving complex nonlinear problems, the validity of the fault diagnosis method of reciprocating compressor piston rod based on harmonic wavelet and manifold learning is proved by actual case data analysis based on BP neural network.

Key words: piston rod, reciprocating compressor, axis orbit, harmonic wavelet, manifold learning

0 Introduction

As the core equipment of industrial equipment, reciprocating compressor is widely used in typical industrial enterprises, such as oil refining, chemical industry, gas extraction. The medium is mostly flammable and explosive gas. Once the reciprocating compressor has a serious failure, such as piston rod fracture and cylinder hitting, it is very easy to cause fire, explosion and other malignant accidents[1]. In China, fault detection and maintenance of piston rods assembly are mainly completed by manual work and correction maintenance method. The fracture failure of piston rod is mainly analyzed by fracture material analysis, including macro analysis, metallographic analysis, chemical composition analysis, mechanical property testing, surface roughness analysis, etc.[2-4]. But these methods cannot be effectively applied on piston rod state of monitoring and fault diagnosis in real time. There have been many studies on on-line monitoring and fault diagnostic methods[5-7]. However, it is difficult for the piston rod to monitor and diagnose because of its complex running state and rapid dynamic change. Therefore, there are few relative methods applied to piston rod.

Currently, only a small number of reciprocating compressors have been installed the on-line monitoring system, and most of them can only monitor a single vertical subsidence of the piston rod. As a result, the operation state of the piston rod cannot be fully reflected. Some scholars have studied the on-line monitoring and early warning technology of piston rod fault. Ma[8], et al. proposed a fault diagnosis method for reciprocating compressors based on the axis orbit of piston rod, and it had solved the problem of insufficient

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information in single direction monitoring method by simultaneously monitoring the X and Y displacement data of the piston rod axis orbit. Wang[9], et al. put forward a method of fault monitoring and diagnosis based on dynamic energy index of piston rod, which had important significance in early warning of piston rod. Xing[10], et al. proposed a fault diagnosis method based on the sensitive feature and artificial neural network, which improved the effectiveness of the piston rod fault early warning.

According to the actual monitoring data of reciprocating compressor piston rod, it can be seen that the piston rod axis orbit is messy and fuzzy. Therefore, it is difficult to extract characteristic parameters directly. There are some problems such as calculating the envelope area of the axis orbit accurately, extracting effective frequency components. In order to obtain the fault sensitive features, it is necessary to reduce the dimension of the high dimensional features of the axis orbit. Therefore, it is necessary to perform filtering, purification and dimension reduction processing to the original axis orbit, and to extract the features that can meet the requirements of actual monitoring and realize rapid fault diagnosis.

This paper is based on the axis orbit purification research results of centrifugal compressor and rotating machinery[11-13]. Harmonic wavelet is used to purify and denoise the axis orbit with its characteristics of 'box' and zero phase shift. After that, features such as vibration energy, natural frequency and the envelope area of the axis orbit are extracted. Based on the characteristics that manifold learning is appropriate for dimension reduction of nonlinear data, then the manifold learning is used to reduce dimension of the axis orbit features and improve the sensitivity of features. The feature extraction and analysis method proposed in this paper is applied to the fault diagnosis of piston rods. And the effectiveness of the method is verified by case data.

1 Feature extraction

1.1 Feature extraction of piston rod axis orbit

The monitoring method of the axis orbit is used to monitor the running state of the piston rod. The sensor installation diagram is shown in Fig. 1.

After obtaining the relative change of the piston rod position R_x and R_y in the horizontal and vertical directions, the actual piston rod axis position (x, y) can be calculated. After obtaining the axial position (x_i, y_i, t_i), $i = 1, 2, \cdots, n$ of the piston rod in a period of time t (for example, one cycle), the curve formed by these coordinate points is the axis orbit of the piston rod

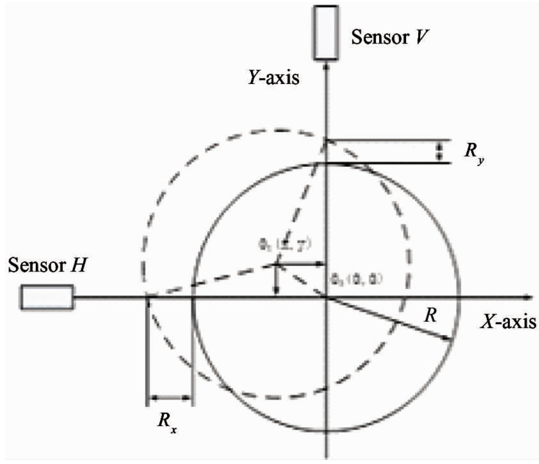

Fig. 1 Sensor installation diagram

at this period. The characteristic parameter set of the axis motion as shown in Table 1 is presented to reflect the operating state of the piston rod[9].

Table 1 Characteristic parameters of axis motion

Number	Characteristic Parameters
1	Axis vibration total energy of piston rod
2	Axis vibration total energy in the X direction
3	Axis vibration total energy in the Y direction
4	Settlement of peak to peak
5	Axis orbit envelope area
6	Axis orbit spectrum energy

In addition, other conventional monitoring characteristic parameters of the reciprocating compressor are extracted, including maximum and minimum jitters of the piston rod in the Y direction and the X direction, the maximum value, minimum value, average value and maximum temperature difference of the cylinder exhaust temperature, average cylinder exhaust pressure, average indicating pressure, average pressure rise rate, crankcase speed RMS, and so on. Considering the difference of vibration energy characteristic values of different devices, it is difficult to formulate a unified alarm limit. Therefore, the energy index calculation method in Ref. [9] is used to eliminate the influence of correlation parameters in features such as the axis vibration energy, spectrum energy and envelope area of the piston rod.

1.2 Harmonic wavelet transform

Harmonic wavelet is a new type of wavelet construct proposed by Newland in 1993. It has frequency-domain box-shaped features and complex filtering results, which can overcome the phenomenon of frequency leakage caused by other binary wavelet transform[14].

Consider the real function $\psi_e(w)$ and $\psi_o(w)$, the harmonic expression of the harmonic wavelet is as follows.

$$\hat{\psi}_e(w) = \begin{cases} \dfrac{1}{4\pi} & -4\pi \leqslant w < -2\pi \\ & \text{and } 2\pi \leqslant w < 4\pi \\ 0 & \text{other} \end{cases} \tag{1}$$

$$\hat{\psi}_o(w) = \begin{cases} \dfrac{i}{4\pi} & -4\pi \leqslant w < -2\pi \\ \dfrac{-i}{4\pi} & 2\pi \leqslant w < 4\pi \\ 0 & \text{other} \end{cases} \tag{2}$$

The inverse Fourier transforms of Eq. (1) and Eq. (2) are carried out, and they are combined into complex functions.

$$\psi(x) = \psi_e(x) + \psi_o(x) \tag{3}$$

The corresponding harmonic wavelet can be defined as

$$\psi(x) = (e^{i4\pi x} - e^{i2\pi x})/(i2\pi x) \tag{4}$$

Using $(2^j x - k)$ $(j, k \in Z)$ instead of x in Eq. (4), it can be seen that the shape of the wavelet does not change, with its horizontal scale being compressed by 2^j, and its position is passed on the new scale by k units ($k/2^j$ units at the original scale). That is, the harmonic wave propagation system of harmonic wavelet is obtained. The number of decomposed layers of the wavelet is determined by the value of j, and the bandwidth of the Fourier transform spectrum is $2^{j+1}\pi - 2^{j+2}\pi$. Let $m = 2^j$, $n = 2^{j+1}$, then the binary expression of the wavelet in the time domain has the general expression:

$$\psi_{m,n}(x) = (e^{i4\pi x} - e^{i2\pi x})/[i2\pi(n-m)x] \tag{5}$$

From Eq. (5) it can be seen that harmonic wavelet does not produce phase shift in the decomposition process, with the function of locking the signal phase. In order to make the process of selecting analysis frequency band more flexible, the value of positive real numbers m, $n(m < n)$ in Eq. (5) is redefined. Considering band $\omega = [2m\pi, 2n\pi]$, the given harmonic wavelet shift step is $k/(m-n)$, the general expression of harmonic wavelet is

$$\psi_{m,n}\left(x - \frac{k}{m-n}\right) = \frac{e^{in2\pi[x-k/(n-m)]} - e^{im2\pi[x-k/(n-m)]}}{i2\pi(n-m)[x-k/(n-m)]} \tag{6}$$

For the time discrete signal $f^d(x)$, $x = 0, 1, 2, \cdots, N-1$ $(N \in Z)$, the harmonic wavelet transform expression is

$$W_f(m,n,k) = \frac{n-m}{N} \sum_{x=0}^{N-1} f^d(x) \psi_{m,n}\left(x - \frac{k}{m-n}\right) \tag{7}$$

The corresponding frequency domain expression is

$$\hat{W}(m,n,\omega) = \hat{f}(\omega)\, \hat{\psi}[(n-m)\omega] \tag{8}$$

where, $\hat{W}(m,n,\omega)$ is the Fourier transform of $W_f(m, n,k)$, $\hat{f}(\omega)$ is Fourier transform of $f^d(x)$, and $\hat{\psi}[(n-m)\omega]$ is Fourier transform of $\psi_{m,n}\left(x - \dfrac{k}{m-n}\right)$. Since the harmonic wavelet has a clear frequency domain expression, it is found the frequency domain is $f^d(x)$ and then $\hat{W}(m,n,\omega)$ is obtained according to Eq. (8). Finally, after the inverse Fourier transform, the signal harmonic wavelet transform $W_f(m,n,k)$ at the scale determined by m, n can be obtained.

1.3 Manifold learning

The local tangent space alignment (LTSA) algorithm in manifold learning is used to reduce dimensionality of high-dimensional characteristics of the piston rod axis orbit. The LTSA constructs local geometric space of low-dimensional manifold by approximating the tangent space of each sample, and then uses local cut space to compute the whole low-dimensional embedding coordinates and obtains dimensioned data. Specific steps are as follows[15].

1) Extract local information. For the high-dimensional feature space matrix $\boldsymbol{X} = [x_1, x_2, \cdots, x_N]$, $x_i \in R^m$ (where $i = 1, 2, \cdots, N$, R^m is m-dimensional space), the k neighborhoods of sample vector x_i are calculated by the European distance method, thus forming local neighborhood matrix $\boldsymbol{X}_i = [x_{i1}, x_{i2}, \cdots, x_{ik}]$.

2) Local linear fitting. A set of orthogonal basis vectors $\boldsymbol{Q}_i$ is chosen to construct the d-dimensional cut space of the neighborhood matrix $\boldsymbol{X}_i$. And the orthogonal projection vector $\boldsymbol{\theta}_j^{(i)} = \boldsymbol{Q}_i^T(x_{ij} - \bar{x}_i)$ of each sample vector $\boldsymbol{x}_{ij}$ $(j = 1, 2, \cdots, k)$ in the neighborhood is calculated, where $\bar{x}_i$ is the neighborhood mean, $\boldsymbol{Q}_i$ is the first d largest left singular vector of $\boldsymbol{X}_i(\boldsymbol{I} - \dfrac{\boldsymbol{e}\boldsymbol{e}^{\mathrm{T}}}{k)}$. $\boldsymbol{I}$ is the unit matrix and $\boldsymbol{e}$ is the unit vector. Geometry in the x neighborhood can be represented by the local coordinates $\boldsymbol{\Theta} = [\boldsymbol{\theta}_1^{(i)}, \boldsymbol{\theta}_2^{(i)}, \cdots, \boldsymbol{\theta}_k^{(i)}]$.

3) Local coordinate integration. Let the local coordinate transformation of the local coordinates be $\boldsymbol{T}_i = [t_{i1}, t_{i2}, \cdots\cdots, t_{ik}]$, then the local reconstruction error is $\boldsymbol{E}_i = \boldsymbol{T}_i(\boldsymbol{I} - \boldsymbol{e}\boldsymbol{e}^{\mathrm{T}}/k) - \boldsymbol{L}_i\boldsymbol{\Theta}_i$, where $\boldsymbol{L}_i$ is the mapping matrix to be determined, and the matrix should satisfy the minimum reconstruction error.

Let $\boldsymbol{H}_i = \boldsymbol{I} - \boldsymbol{e}\boldsymbol{e}^{\mathrm{T}}/k$, then the solution for minimizing the reconstruction error can be expressed as $\min \sum_i \|\boldsymbol{E}_i\|^2 = \min \sum_i \|\boldsymbol{T}_i\boldsymbol{H}_i - \boldsymbol{L}_i\boldsymbol{\Theta}_i\|^2 = \sum_i tr\{\boldsymbol{T}_i\boldsymbol{H}_i\boldsymbol{T}_i^{\mathrm{T}} - \boldsymbol{L}_i\boldsymbol{\Theta}_i\boldsymbol{H}_i^{\mathrm{T}}\boldsymbol{T}_i^{\mathrm{T}} - \boldsymbol{T}_i\boldsymbol{H}_i\boldsymbol{\Theta}_i^{\mathrm{T}}\boldsymbol{L}_i^{\mathrm{T}} + \boldsymbol{L}_i\boldsymbol{\Theta}_i\boldsymbol{\Theta}_i^{\mathrm{T}}\boldsymbol{L}_i^{\mathrm{T}}\}$. Then, when $\boldsymbol{L}_i = \boldsymbol{T}_i\boldsymbol{H}_i\boldsymbol{\Theta}_i^{+}$, the error value is the smallest, where Θ_i^+ is the generalized Moor-Penrose inverse of Θ_i.

Let $T = [t_1, t_2, \cdots, t_N]$, S_i be 0 – 1 selection matrix, then let $T_i = TS_i$, $E_i = T_i H_i (I - \Theta_i^+ \Theta_i)$, $W_i = H_i (I - \Theta_i^+ \Theta_i)$, and introduce the constraint condition $TT^{\mathrm{T}} = I_d$ to obtain the unique solution.

4) Low dimensional global coordinate mapping. The eigenvector corresponding to the $2-(d+1)$ minimum eigenvalue in the $SWW^{\mathrm{T}}S^{\mathrm{T}}$ matrix is the feature data set T after dimensionality reduction.

2 Signal processing and analysis

2.1 Feature extraction based on harmonic wavelet transform

Taking the reciprocating compressor as the object to perform the characteristic processing, it can be seen that the main component of the rod displacement signal concentrated in the low frequency band due to the device running at a lower speed. The 5-layers harmonic wavelet is taken to decompose the axial displacement of the X, Y directions respectively, and the signal bandwidth is $B = 2^{-5} \cdot f_h = \dfrac{5120}{32} = 160\text{Hz}$. Then select the first band (0 – 160Hz) signal for analysis, and the axis orientation in both X and Y directions can be synthesized into the piston rod axis orbit.

Fig. 2 and Fig. 3 are the axis orbit comparison diagrams under normal condition and fracture failure before and after harmonic wavelet purification respectively. It can be seen from the figure that the axis orbit of the piston rod is clearer after harmonic wave purification, and it has a good effect on accurately obtaining the envelope area of the axis orbit. What's more, the fault feature of the axis orbit signal is more significant. The signal characteristic parameters are extracted respectively.

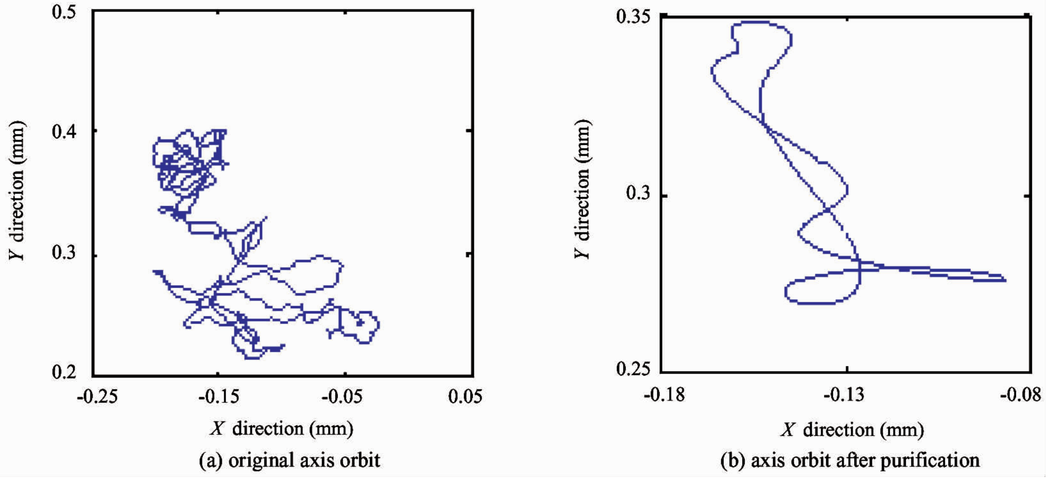

Fig. 2 The piston rod axis orbit comparison diagram under normal operating conditions

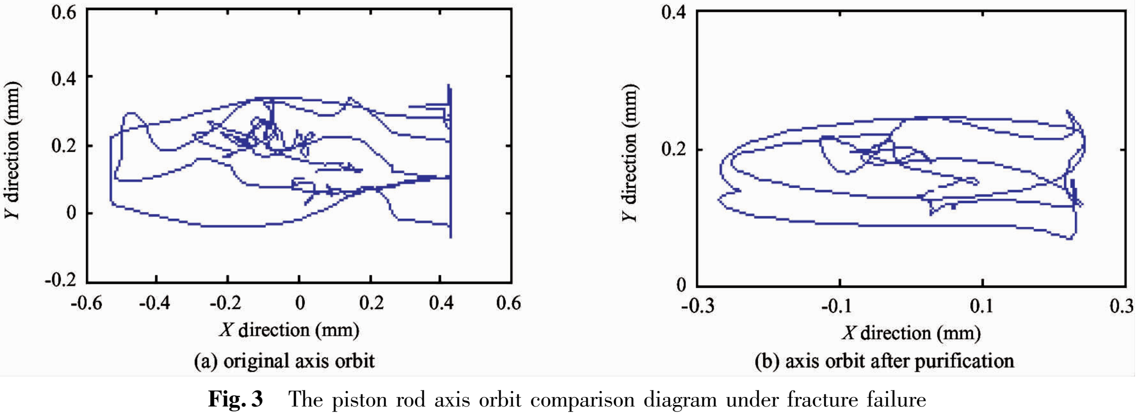

Fig. 3 The piston rod axis orbit comparison diagram under fracture failure

Take the spectrum energy, the total vibration of the axial vibration and the settlement peak-peak as an example, and analyze the effectiveness of the extracted features in the paper. The spectrum energy index of the axis orbit of the piston rod fracture failure is shown in Fig. 4. The spectrum energy is the square sum of the amplitude of the spectrum in the entire frequency band obtained by Fourier transform of the piston rod axis orbit vibration signal. The total axial vibration energy index of piston rod is shown in Fig. 5. According to Fig. 5, after the occurrence of piston rod fracture failure, the piston rod spectrum energy and the overall axial vibration energy are significantly increased with the deterioration of the failure.

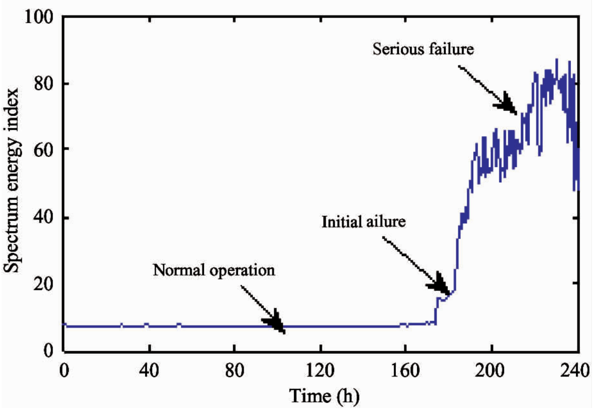

Fig. 4 Spectrum energy index of piston rod fracture failure

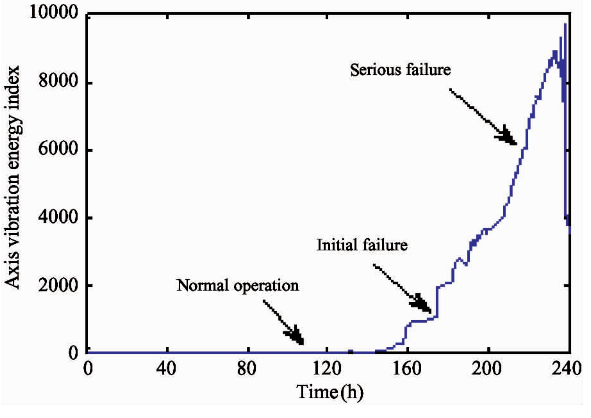

Fig. 5 The total axial vibration energy index of piston rod fracture failure

Piston rod settlement peak to peak change is shown in Fig. 6. It can be seen from Fig. 6 that the settlement peak to peak is only about 0.35mm under the normal operation of the device. However, with the deterioration of the failure, the sedimentation peak to peak continues to increase, and ultimately up to about 0.55mm. Therefore, the settlement peak to peak can effectively monitor and diagnose the failure of the support ring.

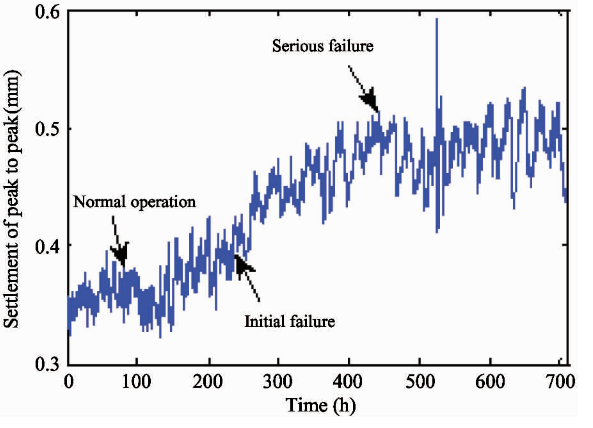

Fig. 6 The settlement peak to peak of piston ring wear failure

The comparison of the parameters extracted by harmonic wavelet and no purification method is shown in Table 2.

Table 2 Comparison of characteristic parameters of piston rod fracture fault

Feature	No purification			Harmonic wavelet purification		
	Normal operation	Initial failure	Serious failure	Normal operation	Initial failure	Serious failure
The overall axial vibration energy index	76.32	256.23	2470.95	32.017	249.945	6203.4
The overall energy index in X direction	45.56	153.45	2012.65	22.570	219.744	5629.8
The overall energy index in Y direction	30.76	102.78	458.3	9.447	38.201	573.6
Axis displacement envelope area	0.0217	0.0609	0.3620	0.0032	0.0129	0.0763
Axis orbit spectrum energy index	40.19	49.27	73.54	7.562	15.279	82.649
Settlement peak to peak displacement	0.3047	0.4753	0.8768	0.2337	0.4125	1.1334

It can be seen that the fault sensitivity of the characteristic parameters after harmonic wavelet extraction is greatly improved, and the change rate of the characteristic parameters before and after the failure is obviously improved and is especially sensitive to the malignant fault. After extracting the characteristic parameters of the axis orbit, the other parameters such as the vibration monitoring and temperature monitoring of the reciprocating compressor are also extracted, therefore the characteristic parameter dimension is high. In order to extract fault sensitive feature, dimension reduction is needed.

2.2 Feature selection based on manifold learning

The LTSA nonlinear manifold learning algorithm is used to reduce the dimension of the axis orbit features and select the sensitive features. In normal working conditions, each of piston rod fastening nut loose fault, piston rod fracture failure and piston support ring, wear failure has 100 samples. After extracting the features of four kinds of working conditions, the features are normalized to eliminate the influence of the magnitude according to

$$\boldsymbol{Y} = (\boldsymbol{X} - X_{\min})/(X_{\max} - X_{\min}) \quad (9)$$

where, $\boldsymbol{X}$ is the original feature matrix, $X_{\min}$ is the minimum value of each feature, $X_{\max}$ is the maximum value, and $\boldsymbol{Y}$ is the new feature matrix obtained by normalization. After the normalization, LTSA is used to reduce the dimension, as shown in Fig. 7. It can be seen from Fig. 7 that the sample data of four different working conditions can be clearly separated after LTSA dimensionality is reduced, which indicated that the sensitive features extracted by LTSA are effective for piston rod fault monitoring. The axis orbit features dimension is reduced by PCA, and the three-dimensional feature results are shown in Fig. 8. It can be seen that the features obtained by PCA cannot be used to identify different faults effectively, and there are individual aliasing state in the samples under different working conditions, which will result in misjudgment of diagnostic results.

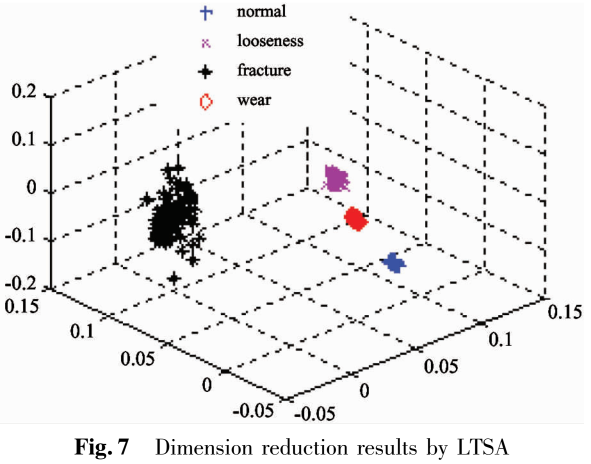

Fig. 7 Dimension reduction results by LTSA

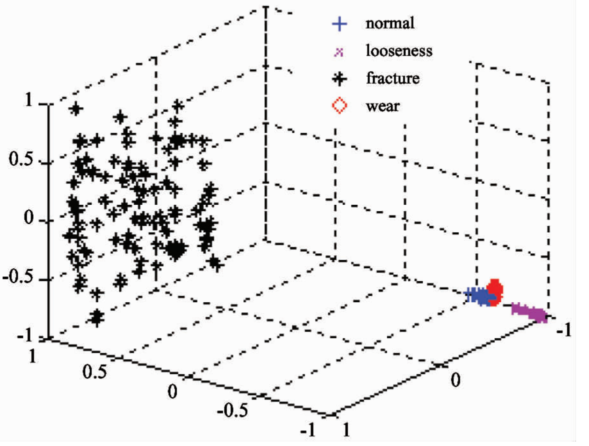

Fig. 8 Dimension reduction results by PCA

3 Actual fault case verification

3.1 Case data and processing flow

The effectiveness of the method is verified by the actual case of reciprocating compressor. The case categories include:

Case 1: The loose failure of piston rod fastening nut;

Case 2: The fracture failure of piston rod;

Case 3: The wear failure of piston supporting ring.

The position of the piston rod sensors is shown in Fig. 9. The online monitoring system can be used to collect piston rod axis orbit signals. The sampling frequency is $f_s = 10240\text{Hz}$, so the analysis frequency is $f_h = f_s/2 = 5120\text{Hz}$. The rated speed of the device is 333rpm. The data processing and verification process are shown in Fig. 10.

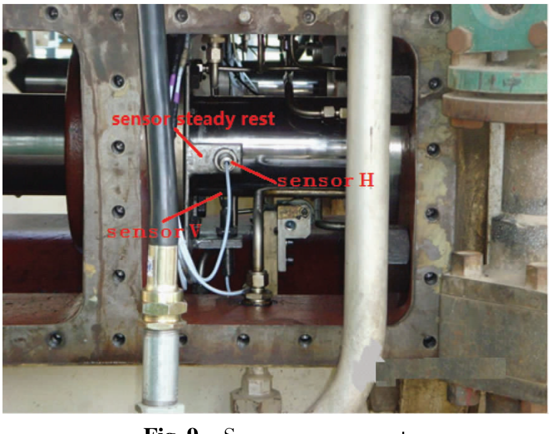

Fig. 9 Sensor arrangement

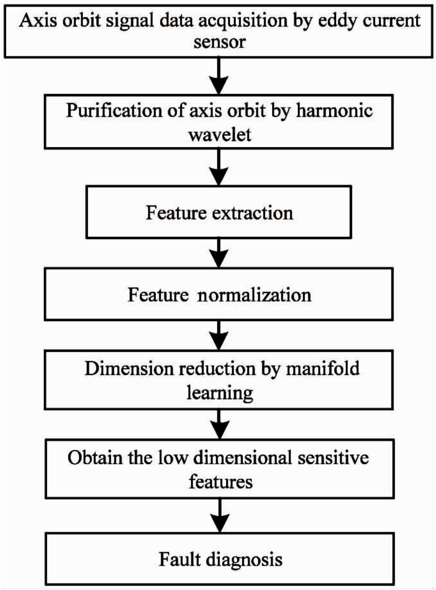

Fig. 10 Data processing and verification flow chart

3.2 Actual data processing and feature extraction results

According to the normal working condition and the three fault cases, the axis orbit of the piston rod is purified by harmonic wavelet at first, and the features are extracted. Then reduce the dimensionality of the features and extract the sensitive features by LTSA.

The training sample features and test sample features after LTSA dimension reduction are shown in Fig. 11 and Fig. 12 respectively. It can be seen from Fig. 11 that after LTSA dimension reduced, the interval between different working conditions is larger in the training samples, and the clustering effect is better between the training samples under the same working conditions. In the test samples, in addition to the mix of a few samples of the fracture failure and the wear failure of supporting ring, the other samples can be clearly separated.

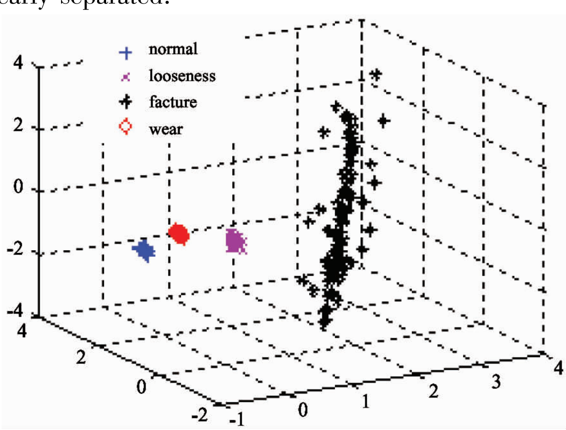

Fig. 11 Training sample features after dimension reduction by LTSA

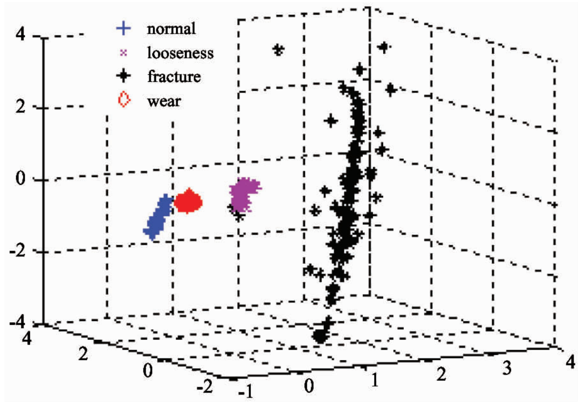

Fig. 12 Test sample features after dimension reduction by LTSA

3.3 Fault recognition based on artificial neural network

Because of the excellent characteristics of neural network, it has been widely successful in many fields, such as pattern recognition, auxiliary analysis, artificial intelligence[16-18]. And the back propagation neural network (BPNN) is currently one of the most widely used neural networks. It has strong nonlinear mapping ability and high self-learning ability. The fault recognition system composed of BPNN has strong fault tolerance[19]. Therefore, the BP neural network is especially suitable for solving complex nonlinear problems, such as the fault diagnosis of piston rod, and its learning process is shown in Fig. 13.

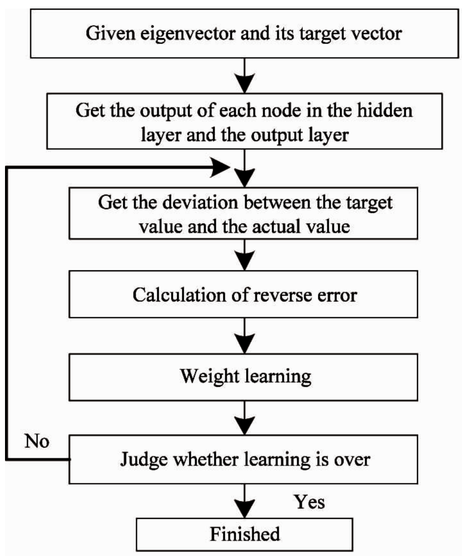

Fig. 13 BP neural network learning flow chart

In order to verify the effectiveness of the proposed method in the fault diagnosis of piston rod, BP neural network is used to identify the fault state. For the four conditions, 100 sets of sample data are selected as training samples and 200 sets of data are used as test samples respectively. After analysis, the number of hidden layers is 8. The sensitive features obtained by harmonic wavelet + LTSA dimension reduction, harmonic wavelet + PCA dimension reduction and PCA dimension reduction are input and trained by BP neural network. The results are shown in Table 3.

Table 3 Actual fault data classification results

Condition	Feature extraction method	Classification accuracy
Normal	Harmonic wavelet + LTSA	100%
	Harmonic wavelet + PCA	100%
	PCA	90%
Fastening nuts loose	Harmonic wavelet + LTSA	100%
	Harmonic wavelet + PCA	89%
	PCA	81%
Piston rod broken	Harmonic wavelet + LTSA	98%
	Harmonic wavelet + PCA	92%
	PCA	83%
Support ring wear	Harmonic wavelet + LTSA	100%
	Harmonic wavelet + PCA	85%
	PCA	76%

It can be seen from Table 3 that:

1) The accuracy of harmonic wavelet + PCA dimension reduction method is higher than that of PCA, and it illustrates the validity of the harmonic wavelet for the piston rod axis orbit purification.

2) The accuracy of the artificial neural network is the highest when the sample data is reduced by harmonic wavelet + LTSA. It is proved that the harmonic wavelet and LTSA method proposed in this paper is effective for fault diagnosis of piston rod.

4 Conclusions

This paper presents a method of feature extraction and analysis of the piston rod axis orbit based on harmonic wavelet and manifold learning. First the piston rod fault sensitive feature is extracted by the harmonic wavelet and manifold learning, then BP neural network is used to classify the actual fault data. The conclusions are as follows.

1) The vibration energy of the piston rod axis orbit can effectively monitor the piston rod fault of the reciprocating compressor. By extracting the vibration energy and the envelope area of the axis orbit, the early signs of failure can be detected timely based on the trend change.

2) Harmonic wavelet algorithm has the ‘lock-in’ function, and able to locate any frequency band that the signal needs to be analyzed. After purified by harmonic wavelet, the fault feature of the piston rod axis orbit signal is clearer, and the fault sensitivity of the extracted feature is also improved.

3) The manifold learning algorithm is suitable for the dimensionality reduction of nonlinear data. It is effective to realize the piston rod fault monitoring by extracting the sensitive features of the piston rod axis orbit by LTSA.

At present, the research on the method of fault monitoring and early warning of reciprocating compressor piston rod is still relatively rare. The proposed method has practical application value for the condition monitoring, early warning and fault diagnosis of reciprocating compressor piston rod.

References

[1] Yu L J. Review on fault diagnosis technology for reciprocating compressors[J]. *Fluid Machinery*, 2014, 42(1): 36-39

[2] Zhan P D, Wang J J, Liu Z, et al. Fracture analysis of piston rod of 4M50 reciprocating compressor[J]. *Plant Maintenance Engineering*, 2015(8): 39-40

[3] Zhu D B, Wang Z W, Pan J D, et al. Fracture analysis on the piston rod of a compressor[J]. *Physical Testing and Chemical Analysis (Part A: Physical Testing)*, 2006, 42(3): 140-143

[4] Lu X F, Ding Y, Gu B Q. Fracture failure analysis of piston rod of hydrogen compressor[J]. *Compressor Technology*, 2004(2): 21-22

[5] Kocyigit N, Bulgurcu H, Lin C X. Fault diagnosis of a vapor compression refrigeration system with hermetic reciprocating compressor based on p-h diagram[J]. *International Journal of Refrigeration*, 2014(45):44-54

[6] Wang Y F, Xue C, Jia X H, et al. Fault diagnosis of reciprocating compressor valve with the method integrating acoustic emission signal and simulated valve motion[J]. *Mechanical Systems and Signal Processing*, 2015(56 - 57):197-212

[7] Wang X, Liu C W, Bi F R, et al. Fault diagnosis of diesel engine based on adaptive wavelet packets and EEMD-fractal dimension[J]. *Mechanical Systems and Signal Processing*, 2013(41):581-597

[8] Ma J, Jiang Z N, Gao J J. Research on fault diagnosis of reciprocating compressor based on the axial position of piston rod[J]. *Journal of Vibration Engineering*, 2012, 25(4):453-459

[9] Wang Q F, Dong L Y, Zhang Y X, et al. Study on fault diagnosis methods based on dynamic energy index of piston rod[J]. *Fluid Machinery*, 2016, 44(9):47-52

[10] Xing, C H, Xu F T, Yao Z Y, et al. A fault diagnosis method of reciprocating compressor based on sensitive feature evaluation and artificial neural network[J]. *High Technology Letters*, 2015, 21(4):422-428

[11] Li S M, Lv G Z, Xu Q Y. On obtaining accurate rotor

sub-frequency signal with harmonic wavelet[J]. *Journal of Northwestern Polytechnical University*, 2001, 19(2): 220-224

[12] Li S M. Harmonic wavelet packets method and used on accurate obtaining the orbit of rotor sub-frequency signal [J]. *Chinese Journal of Mechanical Engineering*, 2004, 40(9):133-137

[13] Zhang W B, Zhou X J, Yang X Y, et al. Rotor axis orbit purification based on harmonic window method[J]. *Journal of Vibration and Shock*, 2009, 28(8):74-77

[14] Newland D E. Harmonic wavelet analysis[J]. *Proceedings of the Royal Society A Mathematical Physical & Engineering Sciences*, 1993(443):203-225

[15] Yang Q, Chen G M, He Q F, et al. Local tangent space arrangement algorithm for early fault diagnosis of bearing [J]. *Journal of Vibration, Measurement & Diagnosis*, 2012, 32(5):831-835

[16] Li Y, Zhang, Y H, Huang X P, et al. Chinese word segmentation with local and global context representation learning[J]. *High Technology Letters*, 2015, 21(1):71-77

[17] Xing Y, Wang Y, Ruan X Y. A neural network approach on reverse engineering surface reasoning in the manufacturing field[J]. *High Technology Letters*, 2001, 7(3): 49-54

[18] Wu T, Yan G Z, Yang B H, et al. EEG classification based on probabilistic neural network with supervised learning in brain computer interface[J]. *High Technology Letters*, 2009, 15(4):384-387

[19] Fan G F, Wang W S, Liu C, et al. Wind power prediction based on artificial neural network[J]. *Proceedings of the CSEE*, 2008, 28(34):118-123

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