A Fault Alarm and Diagnosis Method Based on Sensitive Parameters and Support Vector Machine

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Abstract. Study on the extraction of fault feature and the diagnostic technique of reciprocating compressor is one of the hot research topics in the field of reciprocating machinery fault diagnosis at present. A large number of feature extraction and classification methods have been widely applied in the related research, but the practical fault alarm and the accuracy of diagnosis have not been effectively improved. Developing feature extraction and classification methods to meet the requirements of typical fault alarm and automatic diagnosis in practical engineering is urgent task. The typical mechanical faults of reciprocating compressor are presented in the paper, and the existing data of online monitoring system is used to extract fault feature parameters within 15 types in total; the inner sensitive connection between faults and the feature parameters has been made clear by using the distance evaluation technique, also sensitive characteristic parameters of different faults have been obtained. On this basis, a method based on fault feature parameters and support vector machine(SVM) is developed, which will be applied to practical fault diagnosis. A better ability of early fault warning has been proved by the experiment and the practical fault cases. Automatic classification by using the SVM to the data of fault alarm has obtained better diagnostic accuracy.

1. Introduction
Reciprocating compressor, piston gas engine and reciprocating pump are widely applied in the industry enterprise, but the faults of these machines occurred frequently because of the obsolete fault warning and diagnosis ability. The fault diagnosis of reciprocating machinery represented by reciprocating compressor is the hard task in the field of mechanical fault diagnosis\(^{[1]}\). The fault warning and diagnosis level has been keeping in a relatively weak stage. The accidents of reciprocating compressor would cause serious environment pollution and financial losses.

Study on reciprocating compressor fault diagnosis mainly focus on valve and piping failure. Typical fault diagnosis researches include: the faults of reciprocating compressor valve and driving belt diagnosed by M. Ahmed with the tool of neural networks and support vector machines\(^{[2]}\); the fault diagnosis of valve and bearing studied by L. Jinru with the tool of Wavelet Neural Network and Genetic Algorithm\(^{[3]}\); research on fault diagnosis of reciprocating compressor indicating diagram by
Kun Feng with SVM and PCA\cite{4}. In terms of working principle and efficiency of reciprocating compressor, the efficiency, thermodynamic models and dynamic models have been studied by D. Ndiaye, P. Stouffs, C. Pérez-Segarra and M. Elhaj with theoretical simulation and experimental study\cite{5-8}.

How to applied the online monitoring system in fault diagnosis of reciprocating compressor has always been a hot research spot. The monitoring signals of the online monitoring system of reciprocating compressor have been analyzed and summarized by S.M.Schultheis\cite{9}; the optimized location of sensor installation has been studied by N.K.Verma\cite{10}. In addition, a warning method of online monitoring system has been studied by W.Zhong-Qing\cite{11}; the construction of reciprocating compressor automatic diagnosis expert system has been studied by Zhinong Jiang and has made certain progress\cite{12}.

But the actual level of warning and fault diagnosis of reciprocating compressor has not been improved. How to effectively improve the accuracy of fault warning and realize automatic fault diagnosis is a significant practical and valuable work. Represented by the reciprocating compressor, the criterion of the monitoring warning parameters of reciprocating machinery has not been built. Related standards, such as API and ISO only require the warning parameters in the way of vibration effective value while other monitoring parameters are limited\cite{13-14}. These all lead to low fault sensitivity of warning parameters and low efficiency of online monitoring diagnosis system.

This paper propose a reciprocating compressor fault warning and diagnosis method based on sensitive parameters extracted by scatter matrix method. Experimental and practical fault cases demonstrate that the accuracy and the sensitivity of the new method is superior to the traditional methods. The intelligent fault diagnosis method based on support vector machine achieved the accurate diagnosis result of reciprocating compressor common faults. This new method will improve the practical effect of online monitoring and diagnosis system.

2. Sensitive parameters extraction of reciprocating compressor

2.1. Online monitoring system of reciprocating compressor

At present, the online monitoring system of reciprocating compressor is widely applied. The monitoring signals are composed of key phase, piston rod displacement, crankcase vibration, crosshead acceleration, valve temperature and cylinder dynamic pressure. A set of typical reciprocating compressor online monitoring system is shown in Figure 1.
The new monitoring and alarm parameters with different warning modes of reciprocating compressor are proposed in Table 1. These parameters overcome the weaknesses of original alarm parameters in alarm mode and alarm lines settings. Deteriorate features and relative variation trends of different faults are considered by the warning parameters in Table 1 with using the warning method of absolute value and relative value. It is significant for catching the relative signal changes of early failure. Meanwhile, most of the warning line setup modes are changed to band pass in consideration of the instrument fault signal features in the monitoring system.

| Warning methods of absolute value | Monitoring signal | Warning parameters | Set of warning lines |
|----------------------------------|-------------------|--------------------|----------------------|
| Displacement of piton rod        | Peak-to-peak value of displacement waveform | Band pass |
|                                  | Phase position of displacement waveform | Section alarm |
|                                  | Volatility of displacement average value | Low pass |
| Acceleration of crosshead        | Peak value of acceleration waveform | Band pass |
|                                  | Phase position of acceleration waveform | Section alarm |
|                                  | DC value of acceleration waveform | Band pass |
| Vibration speed of crankcase     | Effective value of velocity waveform | Band pass |
|                                  | DC value of velocity waveform | Band pass |
|                                  | Volatility of velocity waveform effective value | Low pass |
| Valve temperature                | Absolute value of temperature | Band pass |
|                                  | Rate of temperature change | Low pass |

| Warning methods of relative value | Monitoring signal | Warning parameters | Set of warning lines |
|----------------------------------|-------------------|--------------------|----------------------|
| Displacement of piston rod       | Slow changing rate of displacement average value | Band pass |
|                                  | Fast changing rate of displacement average value | Band pass |
| Valve temperature                | Relative temperature value (to other air valve) | Band pass |
|                                  | Relative temperature value (to itself) | Band pass |

2.2. Sensitive parameters extraction algorithm

The multi-source signal fusion is an effective fault diagnosis method due to that the vibration signal characteristics are not obvious in the reciprocating machinery fault diagnosis. Based on practical experience, fault characteristics are summarized to establish the warning parameters which is shown in Table 1 instead of using algorithm directly such as wavelet transform, EMD or PCA. Then the corresponding relations between different failures and corresponding features are studied from fault data based on the distance evaluation method to extract the fault sensitive parameters.

2.2.1 Characteristic assessment technique

The distance assessment technique is relatively improved and simple which evaluates the sensitivity of different features based on the distance between inter-class and intra-class of different characteristics. The sensitive features can be determined when inter-class feature distance of the same patterns is the shortest and intra-class of the different patterns is the longest. The shorter the inter-class distance in same patterns and the longer the intra-class distance in different patterns, the more sensitive the feature will be\(^{[15]}\).

A dimensionless processing method of fault feature is proposed in this paper. Normalization processing is the typical method based on the mean value and the estimated variance value of the data. This method is effective to historical data but unusable when online analyzing the real time data in practical fault diagnosis. The process method is:

\[
V(i, j) = \frac{f(i, j) - N(i, j)}{F(i, j) - N(i, j)}
\]

In the equation:

\(V(i, j)\): the dimensionless value of j feature of number i fault;
\(f(i, j)\): the current value of j feature of number i fault;
\(N(i, j)\): the normal value of j feature of number i fault;
The warning value of feature \( j \) of number \( i \) fault.

The dimensionless value \( V(i, j) \) defined above ranges in \([0, 1]\). Considering the relationship between current parameter value, the historical normal value and warning value of various fault features, the boundary conditions of the mode are:

\[
f(i, j) - N(i, j) \leq 0, \quad V(i, j) = 0; \quad (2)
\]

\[
f(i, j) - F(i, j) \geq 0, \quad V(i, j) = 1. \quad (3)
\]

The distance of the normalized data is calculated when distance assessment is applied to feature selection, so after introducing the warning value, the normalized value can greatly reflect the sensibility of each fault parameters.

The scatter matrix measures the detachable degree of characteristics and patterns by calculating the variance ratio of inter-class and intra-class. The steps of scatter matrix method are shown as follows.

1) Receive all the feature parameters of normal data and the \( m \)-th fault data, and the \( k \)-th fault feature parameter data is recorded as \( P_k \).

2) Calculate the intra-class scatter matrix of the \( k \)-th fault feature parameter:

\[
S_{ik} = \sum_{i=1}^{M} P_i \sum P_i \sum . \quad (4)
\]

Where \( M \) is the number of data categories and is 2, reflect the normal class and fault class. \( P_i \) is the prior probability of class \( i \), \( P_i = \frac{n_i}{N} \). \( n_i \) is the sample number of class \( i \) in the \( k \)-th fault feature parameters. \( N \) is the total sample number of all categories in the \( k \)-th fault feature parameter. \( \sum P_i \sum \) is the intra-class covariance matrix of class \( i \) in the \( k \)-th fault feature parameters and its algorithmic method is:

\[
\sum_i = \frac{1}{n_i} \sum (x_i - \mu_i)(x_i - \mu_i)^T = E[(x_i - \mu_i)(x_i - \mu_i)^T]. \quad (5)
\]

Where \( x_i \) is the value of class \( i \) of the \( k \)-th fault feature parameter, and it is a column vector composed of all values. \( \mu_i \) is the intra-class mean value of class \( i \) in the \( k \)-th fault feature parameters, and its algorithmic method is: \( \mu_i = \frac{1}{n_i} \sum x_i = E(x_i) \). \( tr\{S_{ik}\} \) is the trace of \( S_{ik} \), which is the mean measure of all categories characteristic variance in the \( k \)-th fault feature parameters.

3) Calculate the inter-class scatter matrix of the \( k \)-th fault feature parameters:

\[
S_{ik} = \sum_{i=1}^{M} P_i (\mu_i - \mu_0)(\mu_i - \mu_0)^T. \quad (6)
\]

Where \( \mu_0 \) is the intra-class mean value of class \( i \) in the \( k \)-th fault feature parameters: \( \mu_0 = \sum P_i \mu_i \). Obviously, \( tr\{S_{ik}\} \), which is the trace of \( S_{ik} \), is a measurement of the mean distance between mean value of each class and the global mean.

4) Calculate the hybrid between-class scatter matrix of the \( k \)-th fault feature parameters:

\[
S_{ik} = E[(x - \mu_0)(x - \mu_0)^T] = S_{ik} + S_{ik}. \quad (7)
\]

\( tr\{S_{ik}\} \), which is the trace of \( S_{ik} \), is the variance sum of characteristic values on the global mean.

5) Calculate the guide coefficient \( J_k \) for distance estimation of the \( k \)-th fault feature parameters:

\[
J_k = \frac{tr\{S_{ik}\}}{tr\{S_{ik}\}} \quad (8)
\]

or

\[
J_k = |S_{ik}| / |S_{ik}| S_{ik}^{-1} |S_{ik}|, \quad (9)
\]

or

\[
J_k = tr\{S_{ik}^{-1} S_{ik}\}. \quad (10)
\]
6) For all fault feature parameters, repeat step 1) to 5), then the guide coefficient vector $J$ for distance estimation will be obtained. The vector needs normalization processing to get vector $MJ$. $MJ_k$ is the sensitivity coefficient of the $k$-th feature parameter after calculated by the scatter matrix. And the calculate process is as follows:

$$MJ_k = (J_k - \text{min}(J))/(\text{max}(J) - \text{min}(J)),$$

Where $\text{max}$ represents the maximum value, and $\text{min}$ represents the minimum value. If the element of vector $MJ$ is greater than 0.6, its corresponding fault feature parameter is the sensitive parameter of the $m$-th fault.

3. Experiment and the actual faults test

3.1. Fault experiment

The typical faults of reciprocating compressor include valve fault, moving elements faults and seal assembly faults. The diagnosis method of valve fault is more mature and these faults can be diagnosed in advance by temperature and vibration signals. Due to the weaker damage of the valve fault, few attention is paid to it. So that the fault simulating experiments are composed of three typical faults: the cylinder abrasion, the support ring abrasion and the fracture of piston rod. The cylinder abrasion is difficult to be monitored in actual, due to it is difficult to judge the wear of the cylinder through manual inspection. The fracture of piston rod belongs to the dangerous faults of reciprocating compressor, is hard and dangerous to be simulated. In the experiment, using the vibration protection system to realize the automatic protection and prevent malignant accidents. The Figure 2 and Figure 3 show the experiment process.

Figure 4 shows the signals differences between the faults and common condition. From the crosshead vibration data, different characteristics corresponding to the fracture of piston rod and cylinder abrasion, including acceleration peak value, peak value phase, average peak value. The change trend of some characteristics after normalization are shown in Table 2. In feature extraction, characteristics of crosshead vibration, piston rod displacement, crankcase vibration and temperature were all extracted. Abscissas of Figure 4 represent sampling points, different points corresponding to different rotate speed of the compressor.

![Figure 2](image1.png) **Figure 2** Damaging the surface of supporting ring and piston ring

![Figure 3](image2.png) **Figure 3** Removing the piston rings and support rings of piston
3.2. Sensitive parameters extraction and analysis

In the experiments, aiming at 100 fault samples and 100 common samples taken from the three typical faults, three methods: scatter matrix method, ReliefF method and entropy evaluating method, are applied to extract and comprehensively evaluate the sensitive feature parameters. While the results of ReliefF and entropy evaluating method are used for comparison. The results of all these three methods of sensitive parameters extraction are shown in Figure 5 to Figure 7.

In Figure 5 to Figure 7, the abscissas represent the number of parameters extracted and the ordinate represents the sensitive feature index which is in 0 to 1. Because numbers of measuring points are different, the parameters extracted of faults are also different. It can be seen that the results of ReliefF method are relatively poor, we focus on the scatter matrix method and entropy evaluating method to analysis the results of sensitive parameters extraction.
Figure 5 Schematic evaluation results of the support ring abrasion

Figure 6 Schematic evaluation results of the cylinder abrasion

Figure 7 Schematic evaluation results of the fracture of piston rod

From Table 3, the scatter matrix method has good performance to reflect the sensitivity of characteristic parameters and the result is in consistence with practical experience of fault diagnosis. The extraction result is the most refined, but there are also other sensitive features may be lost. However, this method has the ability of self optimization. With the increase of the actual faults data, the different characteristics of the data will be exhumed and the sensitive parameters extraction will continue to be improved.
Table 3 The extraction results of the Scatter matrix method and Entropy evaluating method

| Fault                  | Scatter matrix method                                      | Entropy evaluating method                                      |
|------------------------|------------------------------------------------------------|---------------------------------------------------------------|
| Support ring abrasion   | 14: the relative variation of the piston rod displacement  | 14: the relative variation of the piston rod displacement      |
|                        |                                                            | 1: the peak-peak value of the piston rod displacement          |
|                        |                                                            | 2, 3: the waveform phase characteristics of piston rod displacement |
|                        |                                                            | 14: the relative variation of piston rod displacement          |
|                        |                                                            | 17, 18: the phase characteristics of cylinder vibration waveform |
|                        |                                                            | 52: RMS of crankcase box vibration                           |
| Cylinder abrasion       | 1: the peak-peak value of the piston rod displacement      | 1: the peak-peak value of the piston rod displacement          |
|                        | 2, 3: the waveform phase characteristics of piston rod displacement | 2, 3: the waveform phase characteristics of piston rod displacement |
|                        | 14: the relative variation of piston rod displacement      | 14: the relative variation of piston rod displacement          |
|                        |                                                            | 17, 18: the phase characteristics of cylinder vibration waveform |
| Fracture of piston rod  | 15: the peak value of cylinder vibration                   | 14: the relative variation of piston rod displacement          |
|                        |                                                            | 18: the phase characteristics of cylinder vibration waveform  |

3.3. Fault automatic diagnosis
The artificial neural network always be used to finish fault automatic diagnosis. Based on the artificial neural network, the inner node weight of fault classifier can be self-amended by the study of case samples. Then it will be equipped with the ability of self-study and self-optimization. The classifier of the artificial neural network will be improved. Considering the different performance of different transducers of each fault, the classifier can be designed as multi-fault classifier and two-fault classifier.

(1) Two-fault classifier
Taking advantage of the sample data of supporting ring abrasion and the cylinder abrasion, each fault sensitive parameters are extracted as above. Using the sample data shown above in this procedure, each fault classifier is trained by each fault sensitive parameters and composed two-fault classifier unit. Then 100 groups of testing data are selected to verify the classified performance, as shown in Table 4.

Table 4 Classification results of two-fault classifier

| Testing data                | the cylinder abrasion | supporting ring abrasion | Piston rod fracture |
|-----------------------------|-----------------------|--------------------------|---------------------|
| Sensitive feature extraction| 99%                   | 97%                      | 98%                 |
| Without extraction          | 86%                   | 81%                      | 88%                 |

The character of the classifier is that all the faults data should be classified by the corresponding specific classifier. For example, cylinder classifier can classify the “abrasion” fault and “non-abrasion”.

(2) Multi-fault classifier
The type of faults in practical diagnosis contains more than two types, so multi-fault classifier is constructed in this paper as well. The union set of sensitive parameters of three faults are collected to train the multi-fault classifier with the same sample data stated above. Then 100 groups of testing data of three faults are tested to show the performance of classifier. The result of the classifier is shown in Table 5, and it illustrates that fault classifier with multi-classifier construction can also process the classification correctly and effectively.

Table 5 Classification results of multi-fault classifier

| Testing data                | the cylinder abrasion | supporting ring abrasion | Piston rod fracture |
|-----------------------------|-----------------------|--------------------------|---------------------|
| Sensitive feature extraction| 95%                   | 97%                      | 100%                |
| Without extraction          | 81%                   | 83%                      | 91%                 |
The data in Table 4 and Table 5 reflect that the fault diagnosis and classification results with sensitive feature extraction in this paper are better than those without sensitive feature extraction. However the faults data is limited, fault classification of reciprocating compressors operating in realistic may not be good enough. The working environment, unit structure and fault characteristics of these reciprocating compressors will be different. As a result, the next work is using sensitive feature extraction method to the online monitoring and diagnosis work of reciprocating compressors. Based on a large number of data, the method will be further tested. Also, the sensitive feature extraction method and classification result will be improved. The improvement flow chart is shown as follows.

![Figure 8 The improvement flow chart](image)

4. Conclusions
Aiming at the weak sensitivity of fault parameters and difficulty of fault automatic diagnosis in reciprocating compressor fault diagnosis, this paper extracts the fault parameters based on the data of online monitoring system. By using the scatter matrix method, the sensitive parameters are extracted from the original features to illustrate the relationship between fault types and fault characteristics. It greatly reduces the process dimensionality of data. The method can also be used to improve the pertinence and effectiveness of warning parameters in online monitoring system.

Based on the fault sensitive parameters, a kind of fault diagnosis framework is built with artificial neural network, and fault typical classifier is trained by experiment data and real fault case data to test the accuracy. The accuracy rate is increased by the sensitive parameters extraction in this paper.

The research proposed in this paper is closely related to the requirements of realistic fault diagnosis of reciprocating compressor, and it has good practical application value. Next, the diagnosis framework proposed in this paper need to be integrated into the online monitoring system to improve
the training of new faults data. The fault warning and diagnosis should be improved to increase the practicability of the online monitoring system.

Acknowledgment
This work was supported by the National Basic Research Program of China (973 Program) under Grant No. 2012CB026000 and the National High Technology Research and Development Program of China (863 Program) under Grant No.2014AA041806.

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