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Research on Fault Recognition for Centrifugal Compressor using Entropy Weight-based Gray Relational Analysis

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Abstract. A new fault recognition method for centrifugal compressor was proposed by using entropy weight-based gray relational analysis (EW-GRA). Firstly, the weight values of all fault features were calculated objectively by the entropy method to avoid the influence of subjective factors. Secondly, an improved local gray relational coefficient (LGRC) formula with weight measures was designed to reflect the contributions of different fault features. Thirdly, according to the relationship between similarity degree and Euclidean distance, the local gray relational distances (LGRD), the global gray relational distances (GGRD) and the global gray relational grades (GGRG) were calculated, and consequently, the fault recognition result was obtained by using the max membership degree principle. Finally, the engineering practicability and validity of the EW-GRA method was demonstrated by a centrifugal compressor fault diagnosis example, and the results show that the EW-GRA method is more effective and accurate than the traditional gray relational analysis (T-GRA) method and the weighted gray relational analysis (W-GRA) method.

Introduction

Centrifugal compressor is one of the major equipment widely used in petrochemical industry. Its catastrophic failures will always paralyze the production line and manufacturing equipments and cause big economic losses, so it is important to investigate the fault diagnosis method.

Up to now, many researchers have investigated the centrifugal compressor fault diagnosis method. Ref.[1] designed a centrifugal compressor health and condition monitoring system based on internal noise spectrum. Ref.[2] developed a BP neural network and a RBF neural network to diagnosis the centrifugal compressor rotor system faults. Ref.[3] developed a centrifugal compressor vibration fault diagnosis method by combining the advantages of wavelet power spectrum and rough set theory. Ref.[4] used experimental study to investigate the centrifugal compressor axial displacement fault and built a self-recovery regulation system. However, because the various faults of the centrifugal compressor are varied and affected by each other, there is not a certainty mapping relationship and obvious action principle between the fault symptoms and fault mechanisms, so these above methods are hard to get good effects especially when the fault sample sizes are small [5,6,7]. In reality, the centrifugal compressor can be regarded as a complex grey system, and it is feasible to introduce grey system theory into the fault recognition field to solve the above problem.

In this paper, an improved entropy weight-based gray relational analysis (EW-GRA) method is developed firstly by integrating the gray set theory and the entropy method, and consequently, a new fault recognition method is proposed based on EW-GRA. And the proposed EW-GRA recognition method is verified by a centrifugal compressor fault diagnosis example, and its performances are compared with that of two other recognition methods.

The rest of this paper is organized as follows: The improved EW-GRA method and the new fault recognition method are proposed in Section 2. The example analysis and performance comparison are stated in Section 3. Finally, the conclusions are summarized in Section 4.

Fault Recognition Method Based on EW-GRA

The gray relational analysis (GRA) is a quantitative analysis to explore the similarity and dissimilarity among factors in developing dynamic process. The theory proposes a dependence to measure the correlation degree of factors; the more similarities develop the more factors correlate. It uses the gray relational grade to measure the relational degree of factors. The procedures of traditional gray relational analysis (T-GRA) are shown in Fig.1. However, the T-GRA method cannot reflect the geometric pattern similarity of the data. To solve this shortcoming, an improved EW-GRA method is developed, and its procedures are shown in Fig.2. And then, the proposed fault recognition method based on EW-GRA is illustrated as follows.

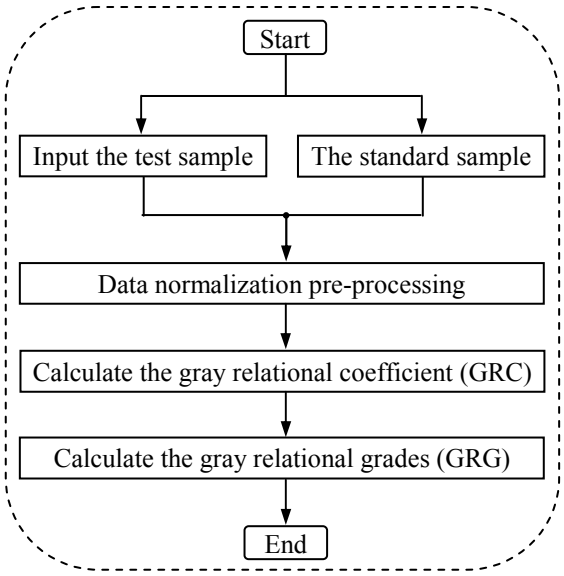

Fig.1. The procedures of the T-GRA method

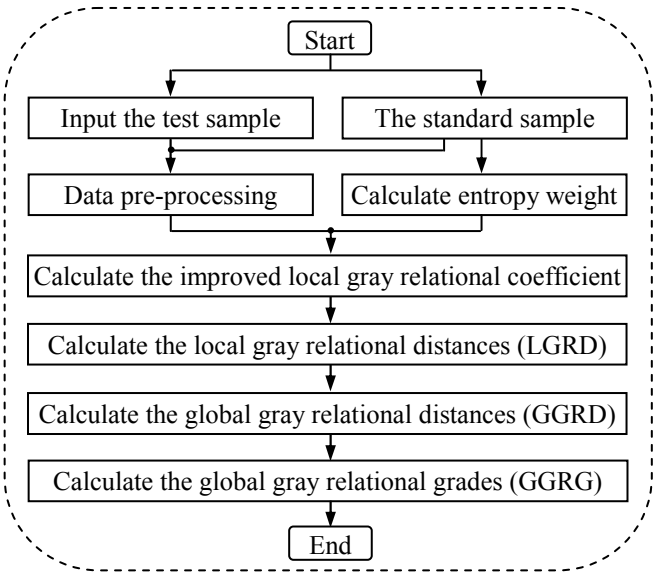

Fig.2. The procedures of the EW-GRA method

Assume the number of original standard fault samples is m, and the number of fault features is n. The original standard fault samples can be expressed by the following series: $X_1, X_2, \ldots, X_i, \ldots, X_m$, and a test fault sample can be expressed by X_0.

$$X_1 = \{x_{11}, x_{12}, \cdots, x_{1j}, \cdots, x_{1n}\} \tag{1}$$

$$X_2 = \{x_{21}, x_{22}, \cdots, x_{2j}, \cdots, x_{2n}\} \tag{2}$$

$$\vdots$$

$$X_i = \{x_{i1}, x_{i2}, \cdots, x_{ij}, \cdots, x_{in}\} \tag{3}$$

$$\vdots$$

$$X_m = \{x_{m1}, x_{m2}, \cdots, x_{mj}, \cdots, x_{mn}\} \tag{4}$$

$$X_0 = \{x_{01}, x_{02}, \cdots, x_{0j}, \cdots, x_{0n}\} \tag{5}$$

where X_i represents the ith standard fault case. X_0 and X_i both includes n elements, and X_{0j} and X_{ij} represent the numeric value of the jth fault feature in the test fault case and the standard fault case, respectively, j=1,2,…n. To enhance the computational efficiency, a fault analysis matrix can be built.

$$Y = \begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_i \\ \vdots \\ Y_m \\ Y_{m+1} \end{bmatrix} = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1j} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2j} & \cdots & y_{2n} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ y_{i1} & y_{i2} & \cdots & y_{ij} & \cdots & y_{in} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ y_{m1} & y_{m2} & \cdots & y_{mj} & \cdots & y_{mn} \\ y_{(m+1)1} & y_{(m+1)2} & \cdots & y_{(m+1)j} & \cdots & y_{(m+1)n} \end{bmatrix} = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_i \\ \vdots \\ X_m \\ X_0 \end{bmatrix} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1j} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2j} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & x_{i2} & \cdots & x_{ij} & \cdots & x_{in} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mj} & \cdots & x_{mn} \\ x_{01} & x_{02} & \cdots & x_{0j} & \cdots & x_{on} \end{bmatrix} \tag{6}$$

Data Normalization Pre-processing. If the values of samples do not obey the three requirements, i.e., non-dimension, scaling and polarization, the fault analysis matrix Y has to be pre-processed to ensure the comparability between all fault features. The normalization pre-processing is taken by Eq.7. After data normalization, the values of samples will be between 0 and 1.

$$y_{ij}^{*}=\frac{\left|y_{ij}\right|}{\sqrt{\sum_{i=1}^{m+1}y_{ij}^{2}}} \qquad i=1,2,\ldots,m+1;\ j=1,2,\ldots,n \tag{7}$$

Calculate the Entropy Weight. The weights for all fault features can be computed by using the entropy method. In information theory, entropy is a measure of how disorganized a system. As applying the concept of entropy to weight measure, a fault feature with a large entropy measure means that it has a great diversity of response, so it has a more signification influence on response.

1) Calculate the ratio p_{ij} of the fault sample data y_{ij}^{*}:

$$p_{ij}=\frac{\left|y_{ij}^{*}\right|}{\sum_{i=1}^{m}\left|y_{ij}^{*}\right|} \qquad i=1,2,\ldots,m;\ j=1,2,\ldots,n \tag{8}$$

2) Calculate the entropy value e_j of the jth fault feature:

$$e_{j}=-\frac{\sum_{i=1}^{m}p_{ij}\ln p_{ij}}{\ln m} \qquad j=1,2,\ldots,n \tag{9}$$

3) Calculate the difference coefficient g_j of the jth fault feature:

$$g_{j}=1-e_{j} \qquad j=1,2,\ldots,n \tag{10}$$

4) Calculate the weight w_j of the jth fault feature:

$$w_{j}=\frac{g_{j}}{\sum_{j=1}^{n}g_{j}} \qquad j=1,2,\ldots,n \tag{11}$$

Calculate the Local Gray Relational Coefficient. Based on the traditional gray relation analysis technique which proposed by Deng, an improved local gray relational coefficient (LGRC) between the standard samples and the test sample is designed to reflect the contributions of different fault features, and its formula is shown as Eq.12.

$$\gamma_{ij}^{l}=\frac{\min\limits_{i\in m}\min\limits_{j\in n}\left\{w_{j}\cdot\left|y_{(m+1)j}^{*}-y_{ij}^{*}\right|\right\}+\xi\cdot\max\limits_{i\in m}\max\limits_{j\in n}\left\{w_{j}\cdot\left|y_{(m+1)j}^{*}-y_{ij}^{*}\right|\right\}}{\left\{w_{j}\cdot\left|y_{(m+1)j}^{*}-y_{ij}^{*}\right|\right\}+\xi\cdot\max\limits_{i\in m}\max\limits_{j\in n}\left\{w_{j}\cdot\left|y_{(m+1)j}^{*}-y_{ij}^{*}\right|\right\}} \tag{12}$$

where i=1,2,…,m and j=1,2,…n, and ξ is the distinguishing coefficient between 0 and 1. Smaller value of the distinguishing coefficient will result in larger range of LGRC, but it will not influence the final priority of standard fault samples. Generally, the distinguishing coefficient can be set as 0.5. And then, the local gray relational coefficient matrix can be built as Eq.13.

$$R^{l}=\begin{bmatrix}\gamma_{11}^{l} & \gamma_{12}^{l} & \cdots & \gamma_{1j}^{l} & \cdots & \gamma_{1n}^{l}\\ \gamma_{21}^{l} & \gamma_{22}^{l} & \cdots & \gamma_{2j}^{l} & \cdots & \gamma_{2n}^{l}\\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots\\ \gamma_{i1}^{l} & \gamma_{i2}^{l} & \cdots & \gamma_{ij}^{l} & \cdots & \gamma_{in}^{l}\\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots\\ \gamma_{m1}^{l} & \gamma_{m2}^{l} & \cdots & \gamma_{mj}^{l} & \cdots & \gamma_{mn}^{l}\end{bmatrix} \qquad i=1,2,\ldots,m;\ j=1,2,\ldots,n \tag{13}$$

Calculate the Local Gray Relational Distance. According to the transfer relation between similarity and distance, the local gray relational distance (LGRD) between X_0 and X_i in the jth fault feature can be computed by Eq.14.

$$d_{ij}^{l}=\frac{1-\gamma_{ij}^{l}}{\gamma_{ij}^{l}} \qquad i=1,2,\ldots,m;\ j=1,2,\ldots,n \tag{14}$$

And then, the local gray relational distance matrix can be shown as below:

$$D^{l}=\begin{bmatrix} d_{11}^{l} & d_{12}^{l} & \cdots & d_{1j}^{l} & \cdots & d_{1n}^{l} \\ d_{21}^{l} & d_{22}^{l} & \cdots & d_{2j}^{l} & \cdots & d_{2n}^{l} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ d_{i1}^{l} & d_{i2}^{l} & \cdots & d_{ij}^{l} & \cdots & d_{in}^{l} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ d_{m1}^{l} & d_{m2}^{l} & \cdots & d_{mj}^{l} & \cdots & d_{mn}^{l} \end{bmatrix} \qquad i=1,2,\ldots,m;\ j=1,2,\ldots,n \tag{15}$$

Calculate the Global Gray Relational Distance. Based on the Euclidean distance formula, the global gray relational distance (GGRD) between X_0 and X_i in entire fault feature spaces can be calculated by Eq.16.

$$d_{i}^{g}=\sqrt{\sum_{j=1}^{n}(d_{ij}^{l})^{2}} \qquad i=1,2,\ldots,m \tag{16}$$

Then, the global gray relational distance vector can be shown as below:

$$D^{g}=\begin{bmatrix} d_{1}^{g} & d_{2}^{g} & \cdots & d_{i}^{g} & \cdots & d_{m}^{g} \end{bmatrix} \qquad i=1,2,\ldots,m \tag{17}$$

Calculate the Global Gray Relational Grade. According to the transfer relation between distance and similarity, the global gray relational grade (GGRG) between X_0 and X_i in entire fault feature spaces can be calculated by Eq.18.

$$\gamma_{i}^{g}=\frac{1}{1+d_{i}^{g}} \qquad i=1,2,\ldots,m \tag{18}$$

Thus, the global gray relational grade vector can be showed as follow:

$$R^{g}=[\gamma_{1}^{g} \quad \gamma_{2}^{g} \quad \cdots \quad \gamma_{i}^{g} \quad \cdots \quad \gamma_{m}^{g}] \qquad i=1,2,\ldots,m \tag{19}$$

Determine the Fault Type. According to the max membership degree principle, the fault type of the test sample is judged as the fault type of the standard sample which has the largest global gray relational grade.

Fault Recognition Example

In this section, we take the centrifugal compressor fault recognition for example to test the validity of the proposed method. Firstly, the vibration signals of typical fault for centrifugal compressor are extracted by wavelet transform, and the characteristics vectors are obtained by using energy. The five standard samples X_1,X_2,…,$X_5$are shown in Table 1, where E_{30}, E_{31},…,E_{37} are eight fault features. And F_1 represents the normal state, F_2 represents rotor unbalance, F_3 represents rotor misalignment, F_4 represents bearing clearance, F_5 represents rub-impact fault, respectively [2].

Table 1. The standard fault samples

No.	Fault Features								State Type
	E_{30}	E_{31}	E_{32}	E_{33}	E_{34}	E_{35}	E_{36}	E_{37}	
X_1	80.9680	4.8781	4.8687	4.8744	4.6534	4.6736	4.8482	4.5560	F_1
X_2	148.6100	8.3382	8.0684	7.8681	7.8395	8.1238	7.9985	8.0348	F_2
X_3	161.2000	8.8342	8.1964	7.7427	8.0342	8.0223	7.9672	7.8739	F_3
X_4	115.8400	12.3530	9.1201	8.0800	8.5177	8.2138	8.2165	8.0797	F_4
X_5	126.0200	8.2789	7.8907	7.8044	8.0527	7.8546	7.8191	7.9284	F_5

Now, the test fault sample X_{31}={73.9060,4.7800,4.6872,5.2256,5.0978, 4.5500,4.7258,5.0198} is diagnosed. After data pre-processing, the six samples X_1,X_2,…,X_5,X_{31} are been normalized as shown

in Table 2, where all fault feature values are between 0 and 1. And then, the weights of eight fault features are computed by using the entropy method, and the results are shown in Table 3.

Table 2. The normalized fault samples

No.	Fault Features								State Type
	E_{30}	E_{31}	E_{32}	E_{33}	E_{34}	E_{35}	E_{36}	E_{37}	
X_1	0.2708	0.2394	0.2707	0.2818	0.2639	0.2689	0.2790	0.2628	F_1
X_2	0.4971	0.4091	0.4487	0.4549	0.4445	0.4674	0.4603	0.4634	F_2
X_3	0.5392	0.4335	0.4558	0.4477	0.4555	0.4616	0.4585	0.4541	F_3
X_4	0.3875	0.6061	0.5072	0.4672	0.4830	0.4726	0.4729	0.4660	F_4
X_5	0.4215	0.4062	0.4388	0.4513	0.4566	0.4519	0.4500	0.4573	F_5
X_{31}	0.2472	0.2345	0.2606	0.3021	0.2891	0.2618	0.2720	0.2895	---

Table 3. The weights of eight fault features

Feature	E_{30}	E_{31}	E_{32}	E_{33}	E_{34}	E_{35}	E_{36}	E_{37}
Entropy value	0.9842	0.9754	0.9878	0.9906	0.9877	0.9883	0.9899	0.9877
Difference coefficient	0.0158	0.0246	0.0122	0.0094	0.0123	0.0117	0.0101	0.0123
Weight	0.1457	0.2268	0.1125	0.0865	0.1137	0.1081	0.0936	0.1133

In Eq.12, let $\Delta_{ij} = w_j \cdot \left| y^*_{(m+1)j} - y^*_{ij} \right|$ be the difference between X_0 and X_i at the jth feature, we can obtain the difference matrix as shown in Eq.20. By comparing the difference values, minmin△=0.0007 and maxmax△=0.0843. Thus, by using Eq.12, the improved local gray relational coefficients can be calculated, and are shown as Eq.21, where the distinguishing coefficient ξ=0.5. And the global gray relational distances are obtained by using Eq.14 and shown as Eq.22. Based on Eq.16 and Eq.18, the global gray relational distance and the global gray relational grade are calculated.

$$\Delta = \begin{bmatrix} 0.0034 & 0.0011 & 0.0011 & 0.0018 & 0.0029 & 0.0008 & 0.0007 & 0.0030 \\ 0.0364 & 0.0396 & 0.0211 & 0.0132 & 0.0177 & 0.0222 & 0.0176 & 0.0197 \\ 0.0425 & 0.0451 & 0.0219 & 0.0126 & 0.0189 & 0.0216 & 0.0175 & 0.0186 \\ 0.0204 & 0.0843 & 0.0277 & 0.0143 & 0.0220 & 0.0228 & 0.0188 & 0.0200 \\ 0.0254 & 0.0389 & 0.0200 & 0.0129 & 0.0190 & 0.0205 & 0.0167 & 0.0190 \end{bmatrix} \quad (20)$$

$$R^l = \begin{bmatrix} 0.9390 & 0.9900 & 0.9890 & 0.9750 & 0.9510 & 0.9975 & 1.0000 & 0.9475 \\ 0.5450 & 0.5236 & 0.6763 & 0.7732 & 0.7156 & 0.6651 & 0.7162 & 0.6922 \\ 0.5055 & 0.4905 & 0.6679 & 0.7820 & 0.7009 & 0.6716 & 0.7182 & 0.7042 \\ 0.6841 & 0.3385 & 0.6127 & 0.7587 & 0.6669 & 0.6593 & 0.7024 & 0.6889 \\ 0.6338 & 0.5279 & 0.6884 & 0.7777 & 0.6995 & 0.6828 & 0.7280 & 0.7001 \end{bmatrix} \quad (21)$$

$$D^l = \begin{bmatrix} 0.0650 & 0.0101 & 0.0111 & 0.0256 & 0.0515 & 0.0026 & 0.000 & 0.0554 \\ 0.8349 & 0.9098 & 0.4786 & 0.2934 & 0.3974 & 0.5036 & 0.3962 & 0.4447 \\ 0.9782 & 1.0388 & 0.4973 & 0.2787 & 0.4268 & 0.4889 & 0.3923 & 0.4201 \\ 0.4619 & 1.9538 & 0.6322 & 0.3181 & 0.4996 & 0.5167 & 0.4236 & 0.4515 \\ 0.5777 & 0.8944 & 0.4526 & 0.2859 & 0.4295 & 0.4645 & 0.3737 & 0.4285 \end{bmatrix} \quad (22)$$

$$D^g = \begin{bmatrix} 0.1041 & 1.6144 & 1.7642 & 2.3306 & 1.4642 \end{bmatrix} \quad (23)$$

$$R^g = \begin{bmatrix} 0.9057 & 0.3825 & 0.3618 & 0.3003 & 0.4058 \end{bmatrix} \quad (24)$$

From Eq.24, we can see that the standard sample X_5 has the largest global gray relational grade. According to the max membership degree principle, the state of the test sample X_{31} can be judged as F_1. And its real result is also F_1, so the recognition result is accurate.

Finally, the probabilities of accurate recognition for twenty test samples are shown in Table 4. It can be seen that the mean probability of accurate of the EW-GRA method is 95.00%, but that of the traditional gray relational analysis (T-GRA) method and the weighted gray relational analysis (W-GRA) method are also 93.33%. Therefore, the EW-GRA method is more effective and accurate than the T-GRA method and the W-GRA method.

Table 4. The probability of accurate recognition (%)

ξ	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	Mean
T-GRA method	90.00	90.00	90.00	90.00	95.00	95.00	95.00	95.00	100.0	93.33
W-GRA method	90.00	90.00	90.00	95.00	95.00	95.00	95.00	95.00	95.00	93.33
EW-GRA method	95.00	95.00	95.00	95.00	95.00	95.00	95.00	95.00	95.00	95.00

Summary

By integrating the gray set theory and the entropy method, an improved EW-GRA method was developed to reflect the geometric pattern similarity of the data.

Based on EW-GRA, a new fault recognition method was proposed, and its engineering practicality and validity was verified by a centrifugal compressor fault diagnosis example. The results show that the EW-GRA method is more effective and accurate than two other GRA methods.

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