Wear 304 (2013) 96–102

Contents lists available at SciVerse ScienceDirect

Wear

journal homepage: www.elsevier.com/locate/wear

A wear particle identification method by combining principal component analysis and grey relational analysis

Jingqiu Wang, Xiaolei Wang*

Jiangsu Key Laboratory of Precision and Micro-Manufacturing Technology, Nanjing University of Aeronautics and Astronautics, Nanjing 210016, China

ARTICLE INFO

Article history:
Received 4 February 2013
Received in revised form
8 April 2013
Accepted 13 April 2013
Available online 9 May 2013

Keywords:
Ferrography
Wear particle identification
Principal component analysis
Grey relational analysis

ABSTRACT

The process to identify wear particles concerns a variety of parameters, some of which may be redundant, and influences the efficiency of computer image analysis. In order to improve the accuracy and speed of debris identification, this paper proposes a new algorithm that combines principal component analysis and grey relational analysis (CPGA). First, principal component analysis is used to optimise the characteristic parameters of wear particles. Then, an improved grey relational analysis is used to discriminate between similar types of wear particles, such as severe sliding and fatigue particles. The experimental results indicate that the CPGA algorithm can successfully solve the information redundancy problem resulting from multiple parameters and proves to be a practical method to identify wear particles quickly and accurately.

1. Introduction

Wear debris from lubricating systems contains detailed and important information about the wear conditions in machines. Presently, oil and debris analysis are still very useful in wear condition monitoring and failure diagnosis in the aerospace industry, mining industry, and even medical fields [1].

Analytical ferrography is used to isolate ferrous debris from lubricant and deposit them on a glass substrate for further analysis using a gradient magnetic field. The advantages to this technique are that debris information including colour, shape, texture, composition, and size distribution can be obtained [2]. This technique is particularly efficient for examining large particles, which is extremely important for monitoring the condition of jet engines [1] and transmissions [3].

Wear particles are the direct consequence of wear processes and their features reflect the wear modes, mechanisms, and severity associated with their generation. The quantity of the debris shows the extent and rate-of-wear progression. The size and size distribution relate to the severity of the wear. Broadly speaking, the size of normal wear particles is less than 15 μm or less than 25 μm for machines used in mining. Furthermore, if the wear mechanisms and specific wear locations need to be determined, a visual inspection of the morphological characteristics such as the shape, colour and texture of wear debris is important [4]. For example, when examining wear particles from severe sliding, cutting, and fatigue, it is critical to find signs of abnormal wear such as adhesive, abrasive and fatigue wear.

Shape characteristics or out-line profiles of the wear particles are important features that can be exploited to identify particles related to on-going wear processes. Some basic shape factors have been proposed for wear particle characterisation [4].

The colour of particles is one important feature that describes both particle materials and the condition of their generation. In one paper [5], an identification method for metallic wear debris using their colour features is presented.

The surface texture shows traces of friction processes and to a certain extent can explain the mechanism behind the type of wear. A statistical approach using co-occurrence matrices is used to describe the texture. The texture parameters capture some of its characteristics, such as homogeneity, coarseness and periodicity.

Much effort has been dedicated to developing a computer-aided image analysis system to reduce reliance on professional and technical personnel and improve the accuracy and efficiency of wear particle identification processes [2,6–11]. However, no matter which means are adopted, it is necessary to decide how many and which parameters should be investigated to ensure an accurate identification of the type of wear debris, and then accordingly to before selecting the most appropriate method for performing an analysis on the debris in question.

In total, there are more than 200 parameters that have been defined to describe appropriate characteristics to distinguish between different types of wear particles. There are many irrelevant features and much redundant information if the wear particle identification process includes a variety of parameters, which have differing levels of significance on wear particle identification. On

* Corresponding author. Tel./fax: +86 25 84893630.
E-mail addresses: wxl@nuaa.edu.cn, xlei_wang@yahoo.com (X. Wang).

0043-1648/$ - see front matter © 2013 Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.wear.2013.04.021

the other hand, it is difficult to classify particles using a single parameter, and for different type of particles, the critical parameters are different. For example, rubbing, cutting and spherical particles have well distinguished boundary morphologies, which include size distributions and shape profile features. Therefore, area, length, roundness and fibre ratio have been chosen for their identification. Roundness is a criterion used for describing a round contour on a spherical particle. The fibre ratio is used to distinguish cutting particles from the other types. After spherical and cutting particles are separated, rubbing particles are easily distinguished from fatigue and severe sliding particles using area and length characteristics because rubbing particles have a much smaller size distribution than fatigue and severe sliding wear particles.

Fatigue and severe sliding wear particles have more complicated boundary morphology and surface structure. Their identification is difficult because of the large number of parameters, some of which are related to each other and some of which are redundant. The two particles shown in Fig. 1 have similar size, shape and outline features, but one of them is a severe sliding particle and the other may be a fatigue particle. The shape and profiles of the particles in Fig. 2 are different, but they are both fatigue particles.

Stachowiak and Peng et al. indicate that a texture-based classification system is a more efficient and accurate way of distinguishing various wear particles than one based on size and shape [12,13]. Therefore, 3D wear particle morphology based on SEM imaging and laser confocal microscopy images are used for wear particle identification [14].

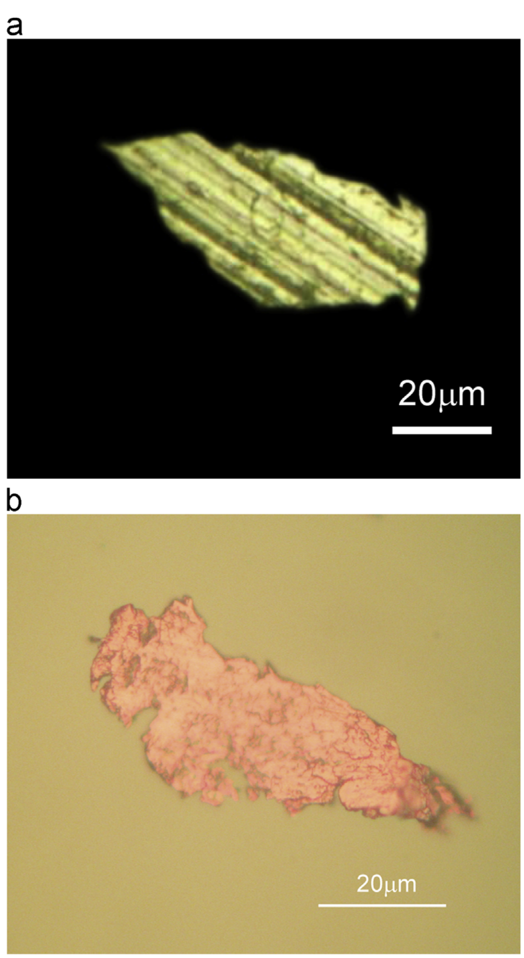

Fig. 1. (a) A severe sliding wear particle (b) a fatigue wear particle.

In order to distinguish between particles that have many similarities, pattern recognition methods have been applied to wear particle analysis. Peng and Kirk utilise grey system theory to perform relational analysis and decision making [15]. This method provides the possibility to identify laminar and severe sliding particles and greatly automate the wear particle identification process. However, the analysis process is still complicated, and the relational grades of different particles, such as fatigue and severe sliding particles, are not substantially different [15].

Neural networks have also been applied to classify wear debris [10,16–19]. However, the application of neural networks is limited by internal problems, such as a large number of simulations, long training time requirements and a lack of system transparency. Furthermore, most of the proposed systems are not finalised prior to practical implementation, and some of them are developed using 3D image analysis, which is difficult to obtain in most fields.

Therefore, we try to deal with multiple parameters and problem of uncertainty to improve the classification quality of wear particles in this paper. Principal component analysis is used to reduce parameter dimensionality and optimise the combination of various characteristic parameters. Grey relational analysis is used to objectively identify the corresponding types of wear particles.

2. Analysis method

In order to improve the accuracy and speed of debris identification, a new algorithm that combines principal component analysis and grey relational analysis (CPGA) is proposed in this paper. As shown in Fig. 3, principal component analysis is first

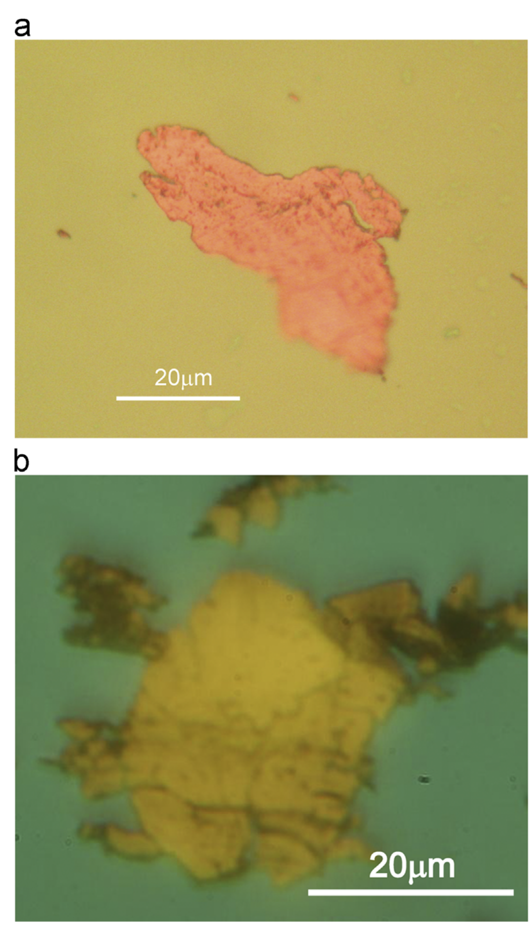

Fig. 2. Two different fatigue wear particles.

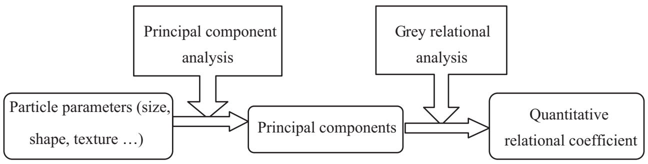

Fig. 3. Schematic flowchart of the CPGA process.

used to solve the information redundancy problem resulting from the use of multiple parameters. Then, in order to reduce the misidentification of wear particles, grey relational analysis is used to distinguish between different types of wear particles.

2.1. Principal component analysis (PCA)

In order to reduce the redundancy associated with multiple parameters in the particle identification process, principal component analysis (PCA) is used to construct the principal components that provide the most significant contribution to identifying certain types of wear particles.

PCA has gradually evolved into an analytical tool for the optimisation of a system with multiple performance characteristics [20–24]. Its main advantage is significantly alleviating the load and complexity of the information by simplifying several correlated variables into fewer uncorrelated and independent principal components, thus preserving as much original information as possible by using linear combinations. In this study, PCA is applied to compress and classify the wear particle multiple parameters. The PCA procedure is described as follows [20,21]:

(1) An original multiple wear particle characteristic array is defined as

$$X=\begin{bmatrix} x_1(1) & x_1(2) & \cdots & x_1(n) \\ x_2(1) & x_2(2) & & x_2(n) \\ \vdots & & & \vdots \\ x_m(1) & x_m(2) & \cdots & x_m(n) \end{bmatrix},\ i=1,2,\cdots,m; j=1,2,\cdots,n,$$

where m is the number of particles, n is the number of the characteristic parameters, and $x_i(j)$ is the jth characteristic parameter of ith particle, such as the major axis length, fibre ratio, energy, and entropy.

(2) The corresponding correlation coefficient array is calculated as

$$R_{jl}=\left(\frac{Cov(x_i(j),x_i(l))}{\sigma_{x_i}(j)\sigma_{x_i}(l)}\right),\ j=1,2,\cdots,n;\ l=1,2,\cdots,n, \quad (1)$$

where $Cov(x_i(j), x_i(l))$ is the covariance of sequences $x_i(j)$ and $x_i(l)$, $\sigma_{x_i}(j)$ is the standard deviation of sequence $x_i(j)$ and $\sigma_{x_i}(l)$ is the standard deviation of sequence $x_i(l)$.

(3) The eigenvalues and eigenvectors are determined from the correlation coefficient array:

$$(R-\lambda_k I_m)V_{ik}=0, \quad (2)$$

where the eigenvalue: $\lambda_k(k=1,2,\cdots,n)$, $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_n \geq 0$ and eigenvectors $V_{ik}=[\alpha_{k1}\alpha_{k1}\cdots\alpha_{kn}]^T$ correspond to the eigenvalue λ_K.

(4) The contribution rate of each component is determined by

$$a_k=\frac{\lambda_k}{\sum_{j=1}^{n}\lambda_j} \quad (k=1,2,\cdots,n), \quad (3)$$

$$AB=\sum_{k=1}^{m}a_k, \quad (4)$$

where a_k is the contribution rate of each component and AB is cumulative contribution rate.

(5) Lastly, the principal components are obtained from

$$Z_{mk}=\sum_{i=1}^{n}x_m(i)\cdot V_{ik}, \quad (5)$$

where Z_{m1} is the first principal component, Z_{m2} is the second principal component, etc. The principal components are aligned in descending order with respect to the contribution rate. Therefore, the first principal component Z_{m1} accounts for most of the contribution rate in the data.

2.2. Grey relational analysis

Grey system theory has proven to be useful for dealing with problems involving poor, insufficient, and uncertain information, such as wear mode recognition [25,26]. The grey relational analysis based on this theory can be further adopted to solve the complicated interrelationships among the designated characteristics. Through this analysis, a grey relational grade is defined and used as an indicator for wear particle classification.

Severe sliding and fatigue particles have similarities that are difficult to distinguish using conventional methods. Therefore, in this paper, we focus mainly on distinguishing between severe sliding and fatigue particles.

The known reference sequence for two types of wear particles are represented as $X_0=(x_{01},x_{02})$, where $x_{0j}(k)$ is the kth characteristic parameter of $x_{0j}(j=1,2)$. The variable X_0 can be represented as

$$X_0=\begin{bmatrix} x_{01}(1) & x_{01}(2) & \cdots & x_{01}(n) \\ x_{02}(1) & x_{02}(2) & \cdots & x_{02}(n) \end{bmatrix}. \quad \begin{matrix} j=1, \text{Severe sliding particle} \\ j=2, \text{Fatigue particle} \end{matrix}$$

Suppose that any unidentified test particles are represented as follows:

$$X=\begin{bmatrix} x_1(1) & x_1(2) & \cdots & x_1(n) \\ x_2(1) & x_2(2) & & x_2(n) \\ \vdots & & & \vdots \\ x_m(1) & x_m(2) & \cdots & x_m(n) \end{bmatrix},$$

where $x_i(j)$ is the jth characteristic parameter of the ith particle, m is the number of particles and n is the number of characteristic parameters.

2.2.1. Grey relational generation

Wear particle parameters have different physical significances and units, resulting in different dimensions and magnitudes of data. Therefore, normalisation is needed prior to beginning a grey relational analysis. The disordered raw data can be transferred to a dimensionless sequence for grey analysis, also known as grey relational generation.

The linear data pre-processing method for the particle characteristics is expressed as

$$x_i^*(k)=x_i(k)/x_{oj}(k),\ i=1,2,\cdots,m; k=1,2,\cdots,n; j=1,2, \quad (6)$$

where $x_i^*(k)$ is the sequence after normalisation, $x_i(k)$ is the original sequence of particle characteristics, $x_{0j}(k)$ is the reference sequence of particles characteristics, m is the number of particles and n is the number of the characteristic parameters.

2.2.2. Grey relational coefficient and grey relational grade

A grey relational coefficient is calculated after grey relational generation [27]. The grey relational coefficient for an unknown particle x_i of the type x_{0j} is defined as follows:

$$\gamma(x_{0j}(k), x_i(k)) = \frac{\Delta_{\min} + \xi\Delta_{\max}}{\Delta_{0i}(k) + \xi\Delta_{\max}},\ 0 < \gamma(x_{0j}(k), x_i(k)) \leq 1, \quad (7)$$

where $\Delta_{0i}(k)$ is the deviation sequence of the reference sequence and the test sequence

$$\Delta_{0i}(k) = |x_{0j}(k) - x_i(k)|;$$
$$\Delta_{\min} = \min_i \min_k |x_{0j}(k) - x_i(k)|; \Delta_{\max} = \max_i \max_k |x_{0j}(k) - x_i(k)|;$$

where ξ is the distinguishing coefficient, which is defined as $0 < \xi < 1$, and is set at 0.5 in this study.

The purpose of defining the distinguishing coefficient is to show the relational degree between the reference sequence $x_{0j}(k)$ and the test sequences $x_i(k)$, where $i = 1, 2, \cdots, m$, $k = 1, 2, \cdots, n$ and $j = 1, 2$.

The grey relational grade is a weighting-sum of the grey relational coefficients and is defined as follows:

$$\gamma(x_{0j}, x_i) = \sum_{k=1}^{n} \beta_k \gamma(x_{0j}(k), x_i(k)), \quad (8)$$

where β_k represents the weighting value of the kth performance characteristic, and $\sum_{k=1}^{n} \beta_k = 1$. In this study, the corresponding weighting values are obtained from the principal component analysis.

Therefore, the grey relational grade, which represents the discriminatory relational level between the test sequence and the reference sequence, can be obtained.

The largest value among $\gamma(x_{0j}, x_i)(j = 1, 2)$ means the test particle is more similar to the jth type. For example, $\gamma(x_{02}, x_i)$ means that the test particle x_i is more similar to the second type, the fatigue particle in this study. Therefore, the conclusion is that x_i may be classified as a fatigue particle or at least that x_i is more likely to be a fatigue particle than a severe sliding wear particle.

2.3. CPGA analysis

As described, severe sliding and fatigue particles have certain similarities that make it difficult to distinguish between them by conventional methods.

Fatigue and severe sliding wear particles have complicated profile morphologies and surface structures. Due to the severe sliding wear mechanism, parallel scratches or grooves often appear on the surfaces of wear particles. Fatigue particle often have a relative homogeneous surface. Therefore, texture parameters are crucial for discriminating between severe sliding and fatigue particles.

In this study, a statistical approach based on the grey level co-occurrence matrices (GLCM) is used to describe the texture of wear particles. The GLCM of an image is an estimate of the second-order joint probability, $P_\delta(i, j)$, of the intensity values of two pixels (i and j), a distance δ apart along a given direction θ, and describes the probability that i and j have the same intensity. This joint probability takes the form of a square array P_δ, with row and column dimensions equal to the number of discrete grey levels (intensities) in the image being examined.

For each wear particle, four co-occurrence matrices are computed with each matrix corresponding to one of the four directions, $\theta = 0°$, $45°$, $90°$, and $135°$, between a pair of adjacent pixels.

In this paper, four of the most commonly used descriptors (energy, contrast, correlation, and entropy) calculated from P_δ are used to extract textural features from the wear particle image data set [28]. These descriptors are described by [29]

$$\text{Energy}: f_1 = \sum_{i=0}^{L-1} \sum_{i=0}^{L-1} \widehat{p}_\delta^2(i, j), \quad (9)$$

$$\text{Contrast}: f_2 = \sum_{n=0}^{L-1} n^2 \left\{ \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} \widehat{p}_\delta(i, j) \right\}, \quad (10)$$

$$\text{Correlation}: f_3 = \frac{\sum_{i=0}^{L-1} \sum_{j=0}^{L-1} ij\widehat{p}_\delta(i, j) - \mu_1\mu_2}{\sigma_1^2 \sigma_2^2}, \quad (11)$$

where the means and variances in the x and y directions are given by

$$\mu_1 = \sum_{i=0}^{L-1} i \sum_{j=0}^{L-1} \widehat{p}_\delta(i, j);\ \sigma_1^2 = \sum_{i=0}^{L-1} (i - \mu_1)^2 \sum_{j=0}^{L-1} \widehat{p}_\delta(i, j); \quad (12)$$

$$\mu_2 = \sum_{j=0}^{L-1} j \sum_{i=0}^{L-1} \widehat{p}_\delta(i, j);\ \sigma_2^2 = \sum_{j=0}^{L-1} (j - \mu_2)^2 \sum_{i=0}^{L-1} \widehat{p}_\delta(i, j). \quad (13)$$

$$\text{Entropy}: f_4 = -\sum_{i=0}^{L-1} \sum_{j=0}^{L-1} \widehat{p}_\delta(i, j) \log \widehat{p}_\delta(i, j). \quad (14)$$

A total of 16 parameters can be used to describe the texture of a particle. Because it is difficult to identify the particle using so many parameters, these parameters need to be optimised.

The step-by-step algorithm to combine the principal component analysis and the grey relational analysis (CPGA) for identification of wear particles is described as follows:

(1) Construct the array of texture parameters.
(2) Obtain the principal components of the texture of a wear particle using principal component analysis.

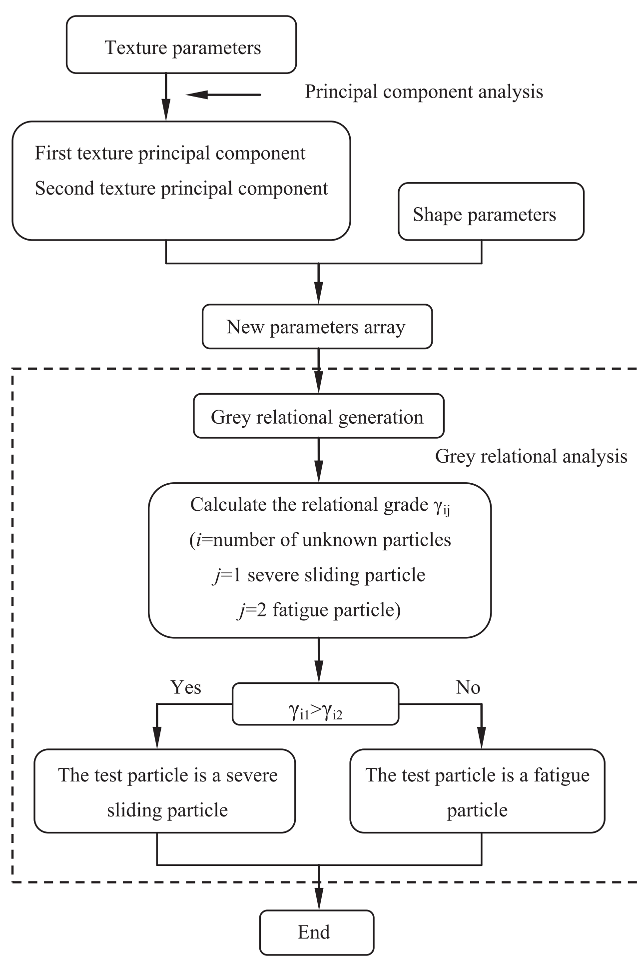

Fig. 4. The flowchart for the CPGA.

(3) Select the principal components for those the cumulative contribution rate is greater than the pre-set threshold value.
(4) Construct a new array using these principal components and shape parameters.
As described by Stachowiak [30], using only the PCA with surface texture parameters may not be sufficient to distinguish between fatigue and severe sliding particles. Therefore, shape parameters (such as the major axis length and fibre ratio) are also included in this array.
(5) Process the grey relational generation for use in the grey analysis.
(6) Calculate the corresponding grey relational grade.

The flowchart of CPGA analysis method is shown in Fig. 4.

3. Test examples

The aim of this work is to classify particles based mainly on their surface texture and shape parameters using the CPGA. More than 60 wear particles taken from mining and petrochemical equipments are examined in this study. The images were obtained

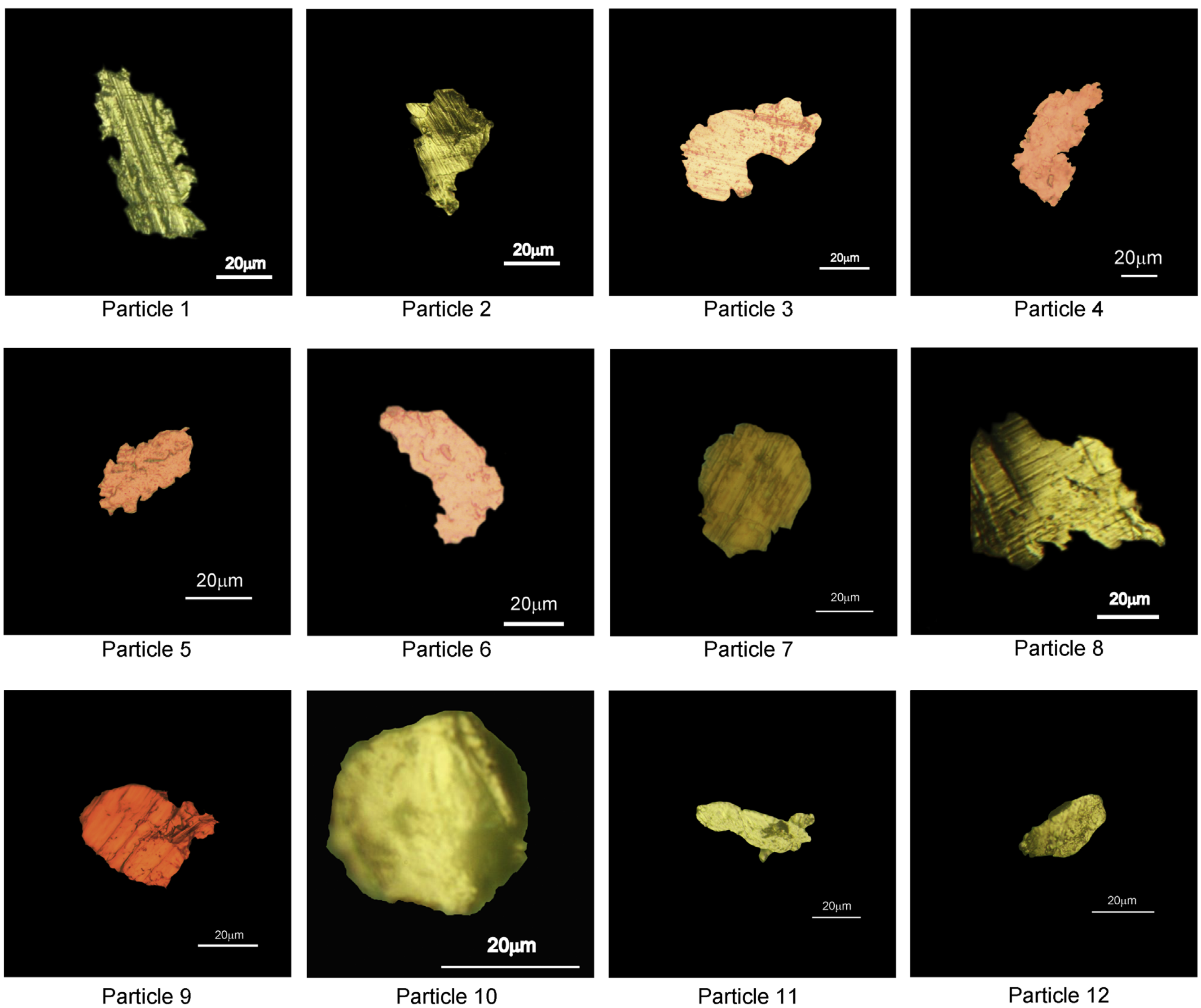

Fig. 5. Examples of wear particles examined in this study.

Table 1
Surface texture parameters of wear particles.

Surface texture	Energy				Contrast				Correlation				Entropy			
Direction	0°	45°	90°	135°	0°	45°	90°	135°	0°	45°	90°	135°	0°	45°	90°	135°
Reference severe sliding particle	0.85	0.85	0.85	0.77	6.71	7.48	6.61	9.88	0.05	0.05	0.05	0.05	059	0.59	0.59	0.54
Reference fatigue particle	0.94	0.80	0.94	0.80	0.86	1.04	0.80	1.19	0.10	0.39	0.10	0.33	0.22	0.25	0.24	0.20
Wear particle 1	0.74	0.74	0.74	0.74	6.51	11.41	4.36	0.03	0.03	0.03	0.03	0.03	1.11	1.16	1.08	1.13

by a digital camera through a ferrograph microscope. Fig. 5 shows 12 example test particles. All the images have the same dimension setting to 600×600.

Typical severe sliding and fatigue particles are selected as references. Examples of surface texture parameters of the reference particles and test wear particles are shown in Table 1.

The principal component analysis is applied to the test wear particles. Four direction texture parameters for energy, contrast, correlation and entropy are analysed. The contribution and cumulative contribution rates of each principal component are obtained and displayed in descending order in Table 2.

The contribution rate of the first principal component is approximately 74%, and the contribution rate of the second principal component is approximately 14%. Because the cumulative contribution rate of the first three principal components is larger than 95%, the three texture principal components are obtained, as shown in Table 3. Then, shape parameters such as the major axis length and the fibre ratio are added to construct a new wear particle parameter array.

The identification results of the wear particles shown in Fig. 5 using the grey relational analysis are displayed in Table 4.

In most cases, the differences between the two relational grades are large enough to classify the particle to its corresponding type. For particle 7 displayed in Table 4, the relational grade is 0.59 for severe sliding and 0.56 for fatigue. These are the closest values in Table 4. In reality, this particle has combined features relating to both a fatigue and a severe sliding particle. The surface texture is not immediately clear and the shape is similar to that of a fatigue particle. This type of particle may be produced by combining rolling and sliding wear in a machine. Another reason for the ambiguity may be the complexities associated with the morphologies of fatigue and severe sliding wear particles.

Hence, the proposed method, which combines principal component analysis and grey relational analysis (CPGA), is capable of distinguishing between severe sliding particles and fatigue particles.

It should be noted that this identification process depends on the reference particle and that wear particles may appear differently for different types of equipment. Therefore, to ensure the accurate identification result, the reference particle needs to be carefully selected to match to the type of equipment and application.

Table 2
The eigenvalues and contribution rates for the principal components.

Principal component	Eigenvalue	Contribution rate (%)	Cumulative contribution rate (%)
First	11.74	73.4	73.4
Second	2.14	13.4	86.8
Third	1.34	8.4	95.2

Table 3
Parameters of wear particles.

Types	Texture principal parameters			Shape parameters	
	1st pc	2nd pc	3rd pc	Major axis length (μm)	Fibre ratio
Particle 1	7.51	−5.48	−11.70	68	1.79
Particle 2	6.59	−5.64	−11.49	45	1.61
Particle 3	7.04	−5.56	−11.45	59	1.46
Particle 4	1.71	−2.25	−3.74	74	1.61
Particle 5	0.71	−1.90	−2.86	35	1.23
Particle 6	0.45	−1.59	−2.16	51	1.27
Particle 7	4.38	−3.16	−6.51	47	1.15
Particle 8	7.09	−3.52	−8.57	73	1.47
Particle 9	4.96	−3.79	−7.72	45	1.25
Particle 10	−0.17	−1.07	−1.17	30	1.08
Particle 11	1.03	−2.05	−3.23	48	2.45
Particle 12	0.49	−1.59	−2.42	30	1.27

Table 4
The relational grade of the severe sliding and fatigue test particles shown in Fig. 5.

Examples	Severe sliding	Fatigue	Identification result
Particle 1	0.86	0.46	Severe sliding
Particle 2	0.90	0.48	Severe sliding
Particle 3	0.95	0.47	Severe sliding
Particle 4	0.44	0.75	Fatigue
Particle 5	0.39	0.88	Fatigue
Particle 6	0.40	0.92	Fatigue
Particle 7	0.59	0.56	Severe sliding
Particle 8	0.90	0.47	Severe sliding
Particle 9	0.64	0.54	Severe sliding
Particle 10	0.36	0.95	Fatigue
Particle 11	0.41	0.83	Fatigue
Particle 12	0.38	0.92	Fatigue

4. Conclusions

This study demonstrates that principal component analysis combined with grey relational analysis can be used for an objective wear particle identification process. The principal component analysis, used to determine the principal surface texture components prior to the grey relational analysis, is capable of solving the information redundancy problem caused by multiple parameters. The grey relational analysis grade is a simple mechanism to provide objective decision making based on the principal components. As a result, the correct discrimination between the most similar particles, severe sliding and fatigue wear particles, is obtained from this algorithm.

This algorithm can be used for an intelligent automated decision making system to reduce the necessity of human experience and judgment in ferrography analyses.

Acknowledgements

This research is supported by the National Natural Science Foundation of China (No. 51205202) and A Project Funded by Priority Academic Program Development of Jiangsu Higher Education Institutions (PAPD).

References

[1] B.J. Roylance, Ferrography—then and now, Tribology International 38 (10) (2005) 857–862.
[2] T.P. Sperring, T.J. Nowell, SYCLOPS—a qualitative debris classification system developed for RAF early failure detection centres, Tribology International 38 (10) (2005) 898–903.
[3] N. Eliaz, R.M. Latanision, Preventative maintenance and failure analysis of aircraft components, Corrosion Reviews 25 (1–2) (2007) 107–144.
[4] S. Raadnui, Wear particle analysis—utilization of quantitative computer image analysis: a review, Tribology International 38 (10) (2005) 871–878.
[5] N.K. Myshkin, H. Kong, A.Y. Grigoriev, et al., The use of color in wear debris analysis, Wear 251 (2001) 1218–1226.
[6] X.P. Yan, C.H. Zhao, Z.Y. Lu, et al., A study of information technology used in oil monitoring, Tribology International 38 (10) (2005) 879–886.
[7] B.J. Roylance, I.A. Albidem, A.R. Luxmoore, The development of a computer-aided systematic particle analysis procedure—CASPA, Lubrication Engineering 48 (12) (1992) 940–946.

[8] U. Cho, J.A. Tichy, Quantitative correlation of wear debris morphology grouping and classification, Tribology International 33 (2000) 461–467.
[9] P. Podsiadlo, G.W. Stachowiak, Development of advanced quantitative analysis methods for wear particle characterization and classification to aid tribological system diagnosis, Tribology International 38 (10) (2005) 887–897.
[10] Z. Peng, An integrated intelligence system for wear debris analysis, Wear (2002) 730–743.
[11] Z. Peng, S. Goodwin, Wear-debris analysis in expert systems, Tribology Letters 11 (3–4) (2001) 177–184.
[12] G.W. Stachowiak, P. Podsiadlo, Automated classification of wear particles based on their surface texture and shape features, Tribology International 41 (1) (2008) 34–43.
[13] G.W. Stachowiak, P. Podsiadlo, Towards the development of an automated wear particle classification system, Tribology International 39 (12) (2006) 1615–1623.
[14] Z. Peng, T.B. Kirk, Computer image analysis of wear particles in three-dimensions for machine condition monitoring, Wear 223 (1998) 157–166.
[15] Z. Peng, T.B. Kirk, Wear particle classification in a fuzzy grey system, Wear (1999) 1238–1247.
[16] Z. Peng, T.B. Kirk, Automatic wear particle classification using neural networks, Tribology Letters 5 (1998) 249–257.
[17] M.S. Laghari, Recognition of texture types of wear particles, Neural Computing and Applications 12 (1) (2003) 18–25.
[18] N.K. Myshkin, O.K. Kwon, A.Y. Grigoriev, et al., Classification of wear debris using a neural network, Wear 203–204 (1997) 658–662.
[19] H.F. Zuo, Z.F. Wu, Z. Yang, Application of double BP-NETWORK in debris identification, ACTA Aeronautica et Astronautica Sinica 21 (4) (2000) 372–375. (in Chinese).
[20] H.S Lu, C.K. Chang, N.C. Hwang, et al., Grey relational analysis coupled with principal component analysis for optimization design of the cutting parameters in high-speed end milling, Journal of Materials Processing Technology 209 (8) (2009) 3808–3817.
[21] C.P. Fung, P.C. Kang, Multi-response optimization in friction properties of PBT composites using Taguchi method and principle component analysis, Journal of Materials Processing Technology 170 (3) (2005) 602–610.
[22] L.K. Pan, C.C. Wang, S.L. Wei, et al., Optimizing multiple quality characteristics via Taguchi method-based Grey analysis, Journal of Materials Processing Technology 182 (1–3) (2007) 107–116.
[23] L.I. Tong, C.H. Wang, H.C. Chen, Optimization of multiple responses using principal component analysis and technique for order preference by similarity to ideal solution, International Journal of Advanced Manufacturing Technology 27 (2005) 407–414.
[24] Z.Y. Lu, X.P. Yan, Y. Peng, et al., Analysis of typical wear particles based on principal component classification, Tribology 28 (5) (2008) 453–456. (in Chinese).
[25] J.P. Fu, Z.Q. Liao, G.Z. Li, et al., Pattern recognition method for wear mode of engine based on the fuzzy grey congnate analysis, Chinese Journal of Mechanical Engineering 16 (24) (2005) 2215–2218. (in Chinese).
[26] S. Chen, Z. Li, Q. Xu, Grey target theory based equipment condition monitoring and wear mode recognition, Wear 260 (4–5) (2006) 438–449.
[27] J.L. Deng, The Primary Methods of Grey System Theory, Huazhong University of Science & Technology Presss82–83.
[28] M.S Laghari, Q.A. Memon, G.A. Khuwaja, Knowledge based wear particle analysis, International Journal of Information Technology 1 (3) (2004) 91–95.
[29] M.H. Bharati, J.J. Liu, J.F. MacGregor, Image texture analysis: methods and comparisons, Chemometrics and Intelligent Laboratory Systems 72 (2004) 57–71.
[30] G.P. Stachowiak, P. Podsiadlo, G.W. Stachowiak, Evaluation of methods for reduction of surface texture features, Tribology Letters 22 (2) (2006) 151–165.