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Wear 225–229 (1999) 1238–1247

WEAR

Wear particle classification in a fuzzy grey system

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Abstract

The analysis and identification of wear particles for machine condition monitoring is usually conducted by experienced inspectors, and, thus, the process is usually very time-consuming. To overcome this obstacle, grey system theory has been applied in this study. The theory of grey systems is a new technique to perform prediction, relational analysis and decision making in many areas. In this paper, the theory of grey relational grades has been used to classify six types of metallic wear debris whose three-dimensional images are acquired from laser scanning confocal microscopy. Their boundary morphology and surface topology are then described by certain numerical parameters. Since the parameters have different levels of significance for different types of wear debris for particle identification, weighting factors of the parameters have been taken into consideration. To determine the weighting factors for the study, fuzzy logic has been applied. This study has demonstrated that a grey system combined with fuzzy logic can be used to classify wear particles satisfactorily. © 1999 Elsevier Science S.A. All rights reserved.

Keywords: Wear particle classification; Machine condition monitoring; Grey system; Relational grade analysis; Fuzzy logic

1. Introduction

Wear particle analysis for machine condition monitoring and fault diagnosis is not a new topic in tribology. The technique has been recognised as an effective and economic method to detect the actual condition of a machine, and furthermore, to allow preventive maintenance to be performed on the machine if it is applicable. However, although wear debris have been studied for several decades, it has been found that the traditional methods have certain shortcomings.

The computer image analysis technique is a solution for some of the problems associated with the conventional techniques, especially for off-line wear particle analysis. So far, these techniques still need to be further developed in some fields. One of the unresolved issues in using computer image analysis techniques is how to effectively describe the characteristics of different types of wear debris using a few numerical parameters so that experts' experience will no longer be a 'bottle neck' in its application. Another issue is how to develop automatic wear particle classification and machine condition monitoring systems for industrial applications.

The technique of describing the characteristics of certain types of wear particles has been investigated in previous studies based on three-dimensional (3D) images [1,2]. With the development of image acquisition technology, it is possible to obtain 3D images of metallic wear debris [1,3]. In this study, laser scanning confocal microscopy (LSCM) [4,5] has been further developed and used to obtain 3D images based on its advantages of adequate resolution and easy operation. A series studies [1,2] has demonstrated that the LSCM can provide appropriate images of metallic wear debris for studying both their boundary morphology and surface topology.

In addition, numerical descriptors have been developed to characterise appropriate features of six types of wear particles, which are rubbing, cutting, spherical, laminar, chunk (as derived from the process of surface fatigue) and severe sliding particles [1,2,6]. Several parameters have been extracted from dozens of options to describe the distinguishing features of these six common types of metallic wear particles before developing an automatic wear particle classification system. The selected descriptors include boundary parameters, which describe the characteristics of sizes and shape profiles of particles, and

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PII: S0043-1648(98)00400-1

surface topology, such as surface roughness and textures. Hundreds of wear particles have been assessed in this study. A database of the six types of wear particles has been set up for further investigation.

Automatic and reliable wear particle classification systems need to be developed so that wear debris can be classified efficiently for machine condition monitoring and fault diagnosis. So far, identifying wear particles has usually been performed by experienced inspectors. This requires considerable experience, and the results may be subjective and depend to some degree on the individual inspector. This has limited the application of these techniques in industry. Nowadays, artificial intelligence methods, e.g., expert systems and neural networks, have provided opportunities to develop automatic wear particle classification systems. Nevertheless, expert systems and neural networks are relatively complicated systems. Researchers need considerable knowledge of them, and, therefore, developing such a system is not easy for most engineers. Grey system theory is a new method, which can be used for such tasks as predicting, controlling and conducting relational grade analysis. In this paper, relational grade analysis has been used to classify wear particles. The theory of grey systems and its application in wear particle classification are stated in the following sections.

2. Wear particles

Oil samples were collected from industrial machines to obtain wear debris for this study. Some details of the machines are shown in Table 1.

Six common types of metallic wear debris, i.e., rubbing, spherical, cutting, laminar, chunk particles (as derived from the process of surface fatigue) and severe sliding wear particles, were selected and studied in this research. These particles were chosen because they have a direct relationship with the wear modes occurring, and their presence can predict or reveal the machine condition [6]. Table 2 is a brief description of the particles, their morphologies, generation mechanisms and related machine condition. The images of the six types of wear particles are shown in Fig. 1.

To study appropriate characteristics of the wear particles effectively and reliably, the Filtergram method [9] was used to separate wear debris from lubricants. The particles were then examined using the LSCM with a transmission sensor [1]. After a pair of 3D images, i.e., the height encoded images and the maximum brightness images, were reconstructed from the original images, the wear particle images were ready to be studied using the developed software [1,2].

3. Three-dimensional wear particle analysis

The images of six types of wear particles were analyzed by studying their boundary morphology and surface topology simultaneously. A total of nine numerical parameters listed in Table 3 were chosen as criteria to describe the features of the wear debris. These nine parameters included five descriptors for boundary morphology, three parameters for surface topology and one volume parameter.

Table 1
The condition of the machines where wear particles were generated and obtained for the study

Serial number of oil samples	Machine information			Oil changed (Y/N)	Total hours	Hours/KMS since oil change
	Make	Model	Compartment			
2-27	TORO	50D	F Differential	N	3731	795
2-33	CAT	785B	R Differential	N	22484	998
2-34	CAT	785B	RTR Final Drive	N	22984	998
2-37	CAT	785B	LT Front Hub	Y	22984	998
2-46	CAT	966D	R Differential	N	1944	–
7-44	CAT	330	LT R Final Drive	Y	4000	4000
8-46	LIEBHR	PR732	Pump Drive	N	–	–
9-29	CAT	777C	RT Front Hub	Y	32014	477
13-46	CAT	789	LT R Final Drive	N	6259	747
13-49	IR	DML-SP	Pump Drive	Y	18909	288
13-50	IR	DML-SP	K Box	Y	18909	288
20-7	CAT	631	F Differential	N	364	–
20-8	CAT	631	RT F Final Drive	N	364	–
20-12	CAT	631	F Differential	N	201	–
20-14	CAT	631	LT F Final Drive	N	201	–
20-2	MITSUB	PAJERO	Trans-PS-Primary	–	4381	4381

– The data were not provided.

Table 2
Wear particles and their relevant information for machine condition monitoring

Type of particles	Morphology	Generation mechanism	Machine condition
Rubbing	Random outlines of boundary shapes; smooth surfaces	The broken parts of the shear mixed layer	Generally normal wear particles, a dramatically increased quantity of the particles in a machine may forecast impending trouble
Cutting	Long, curved particles	Generated as a result of one surface penetrating another (two body and three body abrasive wear)	The presence of individual cutting wear particles is not significant, but the frequent presence of several hundreds of cutting wear particles indicates a severe cutting wear process being under way
Spherical	Like small balls	Generated in the bearing fatigue cracks from rolling bearing fatigue, or cavitation erosion, welding or grinding processes associated with high temperatures [7,8]	The very frequent presence of this type of wear particle gives a warning of impending trouble
Laminar	Thin particles with random outlines of boundary shapes; smooth surfaces with frequent occurrence of holes	Formed by the passage of a wear particle through a rolling contact, probably as a result of the crack between the secondary martensite layer and tempered martensite layer	Generated throughout the life of a bearing. The increased presence of laminar wear debris with severe wear of uncertain origin, indicates a problem with a rolling contact bearing
Chunk	Chunky particles with one flat or worked surface, while the other three perpendicular dimensions are uneven and irregular with a jagged boundary profile	Generated from rolling fatigue and combined rolling and sliding	The presence of chunk particles indicates a high load and/or speed of gears
Severe sliding	A surface with scratches presented in parallel grooved sets	Generated by severe sliding wear	Presence of these particles indicates a breakdown of lubricating films. When these particles appear frequently, it indicates an abnormal machine condition

It is clear that rubbing, cutting and spherical particles have well distinguished boundary morphologies, which include size distributions and the features of shape profiles [6]. Therefore, area, length, roundness and fiber ratio (refer to Table 3 for their definitions) have been chosen to identify them. Roundness is a criterion for describing a round contour of spherical particles, while fiber ratio can be used to identify cutting particles from the others. After spherical and cutting particles are separated from the other particles, rubbing wear particles are easily distinguished from laminar, chunk and severe sliding particles using two parameters—area and length. This is because rubbing particles have much smaller size distribution than do the latter's.

Laminar, chunk and severe sliding wear particles have more complicated boundary morphology and surface structure than that of rubbing, cutting and spherical particles. To identify them, fractal dimension, H.A.R., R_a, R_q and γ^2 (see Table 3 for the definitions) have been selected to characterize their distinctive features in this study. Since laminar particles often have a random outline of shape profiles, and chunk and severe sliding particles have one or more worked edges, the fractal dimension can describe this feature effectively. H.A.R. is used to separate laminar particles from chunk particles based on their different morphologies in three-dimensions. However, it may not be easy to obtain reliable H.A.R. in practice. Thus, R_a and R_q have been applied to help the identification of laminar and chunk debris based on the fact that laminar particles often have a smoother surface than that of chunk particles. γ^2 is a parameter to assess surface textures. It is crucial for identifying severe sliding particles from laminar and chunk particles. The choice of this parameter relies on the fact that severe sliding wear debris usually have parallel

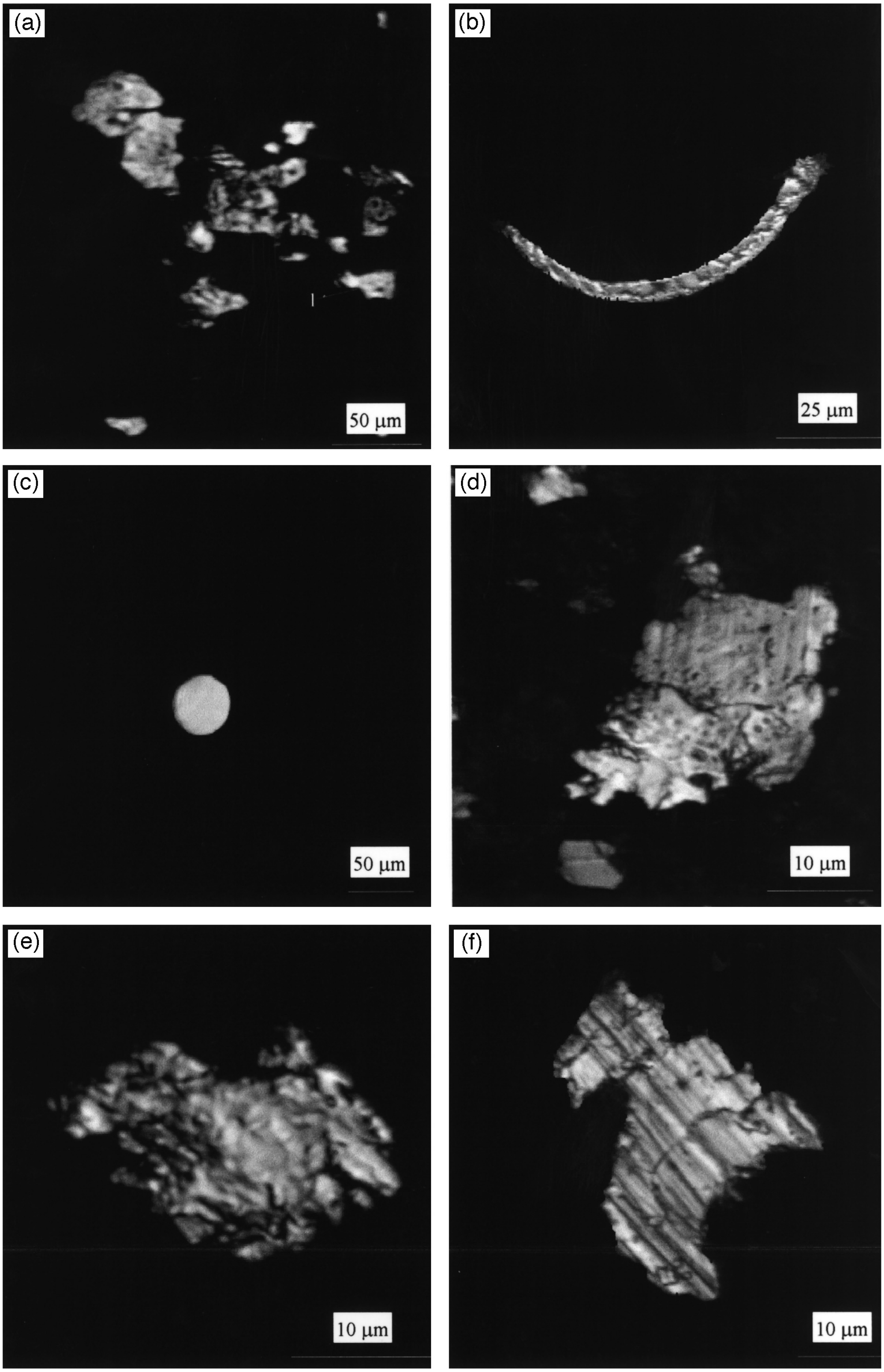

Fig. 1. Examples of wear debris: (a) rubbing particles, (b) a cutting particle, (c) a sphere which is not generated from a machine, but demonstrating the same features as a spherical particle, (d) a laminar particle, (e) a chunk particle (as derived from the process of surface fatigue), (f) a severe sliding particle.

scratches or grooves on the surfaces due to severe sliding wear mechanism [2].

More than 60 wear particles of each type have been investigated in this study. The database was built using

Table 3
Three-dimensional analysis results of wear particles

Parameters	Types of wear particles					
	Rubbing	Spherical	Cutting	Laminar	Chunk	Severe sliding
Area (μm^2)	34	659	227	1593	1085	813
Length (μm)	8	14	38	52	47	40
Roundness	0.58	0.89	0.11	0.57	0.52	0.54
Fiber ratio	1.42	0.84	12.15	2.86	3.22	3.75
Fractal dimension				1.137	1.125	1.123
H.A.R.				0.125	0.226	0.196
R_a (μm)				0.757	1.228	0.957
R_q (μm)				0.946	1.535	1.196
γ^2				0.619	0.614	0.275

Area (μm^2): area measurement of wear particles.
Length (μm): length in the major dimension.
Roundness ($4(\text{area})/\pi(\text{length})^2$): the roundness is sensitive to the elongation of a boundary profile. The roundness is equal to 1 for a circle and is less for any other shape.
Fiber ratio: it is approximately equal to the length of a fiber along its axis divided by its width. Fiber ratio is aspect ratio (length/width) if the center point is in the contour of a image.
Fractal dimension (FD): numerical parameter used for characterisation of a boundary profile or curve. $D = 1 - \mathrm{d}x/\mathrm{d}y$, where $\mathrm{d}x/\mathrm{d}y$ is the gradient of a double log plot of dilation radius and perimeter.
H.A.R. (height aspect ratio): the height of a particle compared to its maximal planer dimension.
R_a: average roughness of a surface.
R_q: root mean square of R_a.
γ^2: spectral moment analysis is a quantitative descriptor which can indicate the texture pattern, i.e., isotropy and anisotropy. For isotropic surfaces, γ^2 is normally greater than 0.5, while γ^2 is less than 0.3 for anisotropy.

their average values. The results of 3D computer image analysis of the wear particles are displayed in Table 3.

4. The relational grade of grey system theory

Grey system theory was advanced by Deng [10] in the 1980s. The system was named by using grey as the color which indicates the amount of known information in control theory. For instance, if the internal structures and features of a system are completely unknown, the system is usually denoted as a ‘black box’. In contrast, ‘white’ means that the internal features of a system are fully explored. Between white and black, there is a grey system indicating that part of the information is clear, while another part is still unknown.

Grey system theory has been successfully applied in engineering prediction and controlling, social and economics systems, and agriculture systems [10–14] in recent years. The technique has certain distinct advantages, such as having simple processes to study complex systems and providing reliable analysis results. There are four major directions among the current applications. The first one is grey relational analysis, applied in agriculture and fault diagnosis in engineering [11,13]. The second is grey prediction and forecasting using a differential model denoted as the GM(1,1) grey forecasting model [10]. The next is the decision making of a grey element or decision making combined with the GM(1,1) model. Finally, grey controlling is often applied in industry and other daily-used products, for example, washing machines [10]. In this paper, wear particles will be classified using relational grade analysis.

4.1. Relational grade analysis

Grey relational analysis is used to study stochastic data and detect their relationship with affected factors. In this study, it is applied to classifying unknown wear particles into six groups, i.e., rubbing, spherical, cutting, laminar, chunk and severe sliding particles. Here, the known information is the reference patterns represented as a set of centroids of the six types of wear particles (Table 3): $X_0 = \{x_{01}, x_{02}, \ldots, x_{06}\}$, where $x_{0k}(j)$ is the jth (measured) feature of x_{0k} ($k = 1, 2, \ldots, 6$; $j = 1, 2, \ldots, 9$). X_0 can be represented as follows:

$$X_0 = \begin{array}{c@{}l} \begin{array}{cccc} \text{Area} & \text{Length} & \cdots & \text{H.A.R.} \end{array} & \\ \left[\begin{array}{cccc} x_{01}(1) & x_{01}(2) & & x_{01}(9) \\ x_{02}(1) & x_{02}(2) & & x_{02}(9) \\ \vdots & & & \vdots \\ x_{06}(1) & x_{06}(2) & \cdots & x_{06}(9) \end{array}\right] & \begin{array}{l} \text{Rubbing particle} \\ \text{Spherical particle} \\ \vdots \\ \text{Severe sliding particle} \end{array} \end{array}$$

Suppose that test data are available in the form of a set of vectors: $\boldsymbol{X} = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_n\}$, where $\boldsymbol{x}_k$ is a feature vector representing an unknown particle i, and $x_i(j)$ is the jth parameter of x_i. Then, the task is to classify x_i ($i = 1, 2, \ldots, n$) into k subsets ($k = 1, 2, \ldots, 6$) by calculating and comparing the relational coefficients using the reference data and the test data. The relational coefficient

Table 4
Weights of the nine parameters for the six types of particles

Types of particles	Area	Length	Roundness	Fibre ratio	FD	γ^2	R_a	R_q	H.A.R.
Rubbing	0.50	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Spherical	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00
Cutting	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00
Laminar	0.00	0.00	0.00	0.00	0.10	0.50	0.05	0.05	0.30
Chunk	0.00	0.00	0.00	0.00	0.10	0.40	0.20	0.10	0.20
Severe sliding	0.00	0.00	0.00	0.00	0.10	0.80	0.05	0.05	0.00

between the centroid of the kth type of wear particle ($k = 1, 2, \ldots, 6$), and test pattern x_i is calculated as:

$$\xi_{ik}(j) = \frac{\Delta_{\min} + \rho\Delta_{\max}}{\Delta_{ik}(j) + \rho\Delta_{\max}}, \tag{1}$$

where $\xi_{ik}(j)$ is called the relational coefficient of unknown pattern x_i to the centroid of type k for jth descriptor, and $i = 1, 2, \ldots, n$, $j = 1, 2, \ldots, 9$, and $k = 1, 2, \ldots, 6$;

$$\Delta_{ik}(j) = |x_{0k}(j) - x_i(j)|;$$

$$\Delta_{\min} = \min_i \left\{ \min_j |x_{0k}(j) - x_i(j)| \right\};$$

$$\Delta_{\max} = \max_i \left\{ \max_j |x_{0k}(j) - x_i(j)| \right\};$$

ρ is the recognition coefficient, $\rho = (0.1\text{–}1.0)$ and typically $\rho = 0.5$.

The original grey relation grade between the test pattern x_i and type k is derived from:

$$\gamma_{ik} = \frac{1}{9}\sum_{j=1}^{9} \xi_{ik}(j), \tag{2}$$

$i = 1, 2, \ldots, n$; $j = 1, 2, \ldots, 9$; $k = 1, 2, \ldots, 6$.

Therefrom, the six grey relational grades, which are the discriminatory relational measurement of a test pattern to rubbing, spherical, cutting, laminar, chunk and severe sliding particles, can be obtained. The largest one among γ_{ik} ($k = 1, 2, \ldots, 6$), for example γ_{i2}, means the test pattern x_i is more similar to the second type (spherical debris) than to other types. So the conclusion is that x_i may be classified as a spherical particle, or at least, x_i is more likely to be a sphere than to be other types of wear particles.

There are unresolved problems in the above investigation. The first issue is to put uniform weight on each parameter $x_i(j)$ ($j = 1, 2, \ldots, 9$) for all types of particles in Eq. (2). The reason of re-considering the weighting factors is because the different parameters may have different levels of significance on the classification of the six types of wear particles. Therefore, the weighting factors should be considered when calculating the grey relational grades instead of using the same weighting factor for all parameters. Another issue in the study is how to scale various ranges of data into a comparable scale, normally in $[0 \sim 1]$. This is a common topic in the study of multi-dimensional data analysis. The details of re-scaling data and utilising fuzzy logic to determine the weights in this study will be illustrated individually.

4.2. Determining weighting factors using fuzzy logic

Fuzzy logic was invented by Zadeh et al. [15] in 1964. The development of fuzzy logic has broken through the obstacles of conventional logic, which divides the world into yes and no, black and white [16]. Fuzzy logic is more similar to the thinking processes of human brains, dealing with uncertain issues most of the time. Although meeting with scorn by American companies and the academic community at the beginning, the concept of fuzzy logic has been finally accepted and applied to daily life products, such as cars and computers. It should be mentioned here that using fuzzy logic in computer science makes computers simulate the thinking process of human beings, and its applications have brought dramatic changes in many areas [17–20].

The weighting factor of a parameter indicates the significance of one parameter to a single class. Weighting factors have been commonly used in fuzzy clustering systems [18], which are subject to:

$$\sum_{j=1}^{c} w_{ij} = 1, \tag{3}$$

where $1 \le i \le n$, $1 \le j \le c$, $w_{ij} \ge 0$, and w_{ij} is the membership of the jth descriptor in the ith class. Since the

Table 5
An example of the multi-dimensional issue of the study

	Area (μm^2)	Length (μm)	Roundness	Fibre Ratio	FD	H.A.R.	R_a (μm)	R_q (μm)	γ^2
Reference data	1593	52	0.57	2.86	1.137	0.125	0.757	0.946	0.619
Test data	487	34	0.55	3.27	1.025	0.110	0.870	1.088	0.522

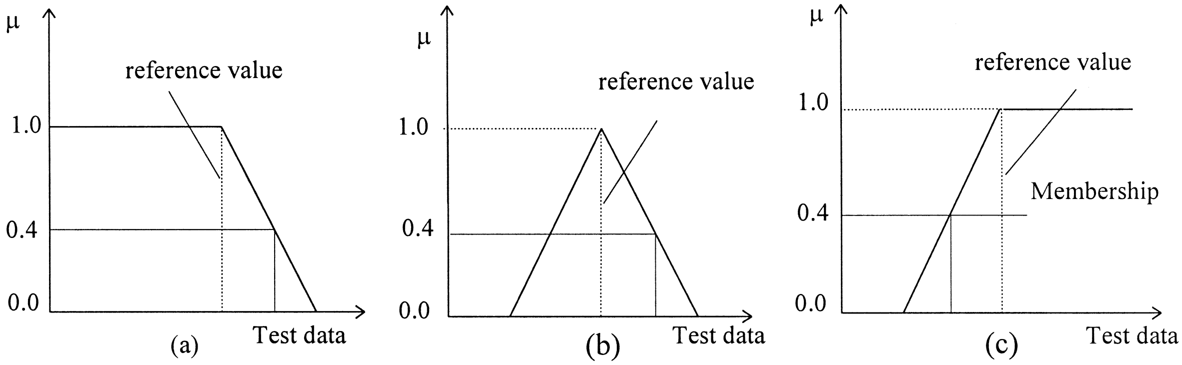

Fig. 2. The schematics of determining the membership of a feature to the reference value: (a), (b) and (c) are three different formats.

significance of a descriptor to a type of wear particle is normally an uncertain concept, fuzzy logic has been used to transfer vague expressions, such as very important, important, less important and no effect, into a partial membership representing in $[0 \sim 1]$. Therefore, the first task in determining the weighting factors is to find out the significance of the parameters to each class. According to the characteristics of those six types of metallic wear debris, a total of nine parameters have been chosen to describe their boundary morphology and surface topology. The importance levels of the nine descriptors in the classification were determined by experience [21,22]. For instance, it is believed that roundness is a crucial parameter to identify spheres. So we put the level 'very important' to roundness for spherical particles. Then, the oral expressions of significance were converted into figures being subject to Eq. (3). Tests have been done afterwards to check if the determined weighting factors are suitable for the task or not. If the results do not match with identification of experienced inspectors, the weighting factors need to be modified until the identification results of the developed system are harmony with human judgement. As a result, the final weights are shown in Table 4. Accordingly, Eq. (2) for calculating the grey relational grade is then modified as:

$$\gamma_{ik} = \frac{1}{9} \sum_{j=1}^{9} \xi_{ik}(j) \times w_{ij}, \tag{4}$$

where w_{ij} is the weighting factor of descriptor j for unknown pattern x_i, and $W = \{w_{ij}\}$ is displayed in Table 4.

4.3. Re-scaling test data

To illustrate the multi-dimensional issue of this study, examples of test data and reference values are shown in Table 5. Studying the data in Table 5, it is clear that some data, such as area and length, are up to thousands of times greater than others (e.g., roundness, H.A.R., R_a, etc.) (refer their definitions to Table 3). If the data are not scaled to a comparative range, small data will be ignored when calculating the relational coefficient in Eq. (1).

The issue of scaling the data is not a pure normalisation problem [23]. It involves proper methods on how to measure the similarities of test data to the reference data. So

Table 6
The calculating schematics of the nine parameters to the centroids of six types of wear debris

Types of particles	Area	Length	Roundness	Fiber ratio	FD	γ^2	R_a	R_q	H.A.R.
Rubbing	a	a	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Spherical	N/A	N/A	c	N/A	N/A	N/A	N/A	N/A	N/A
Cutting	N/A	N/A	N/A	c	N/A	N/A	N/A	N/A	N/A
Laminar	N/A	N/A	N/A	N/A	b	a	b	b	a
Chunk	N/A	N/A	N/A	N/A	b	a	b	b	c
Severe sliding	N/A	N/A	N/A	N/A	b	c	b	b	N/A

N/A means that the parameters will not be considered in the calculation. It has the same meaning as weight factor = 0.0 in Table 4, which indicates that the parameter does not affect the identification of certain type of wear debris;
a, b and c refer to three schematics shown in Fig. 2.
The schematics are determined based on the widely used normalization methods and the practical situation of this classification. For instance, if consider the membership of roundness parameter to spherical particles, c schematic needs to be used. The reason is that if the roundness value of a particle (test value) is equal to or greater than the reference value of spheres, the membership should be set to 1.0. It indicates the test particle has a rounder or very similar contour than do the reference sphere. Similar to this example, the schematics of the parameters to each type of wear particle have been decided for the classification.

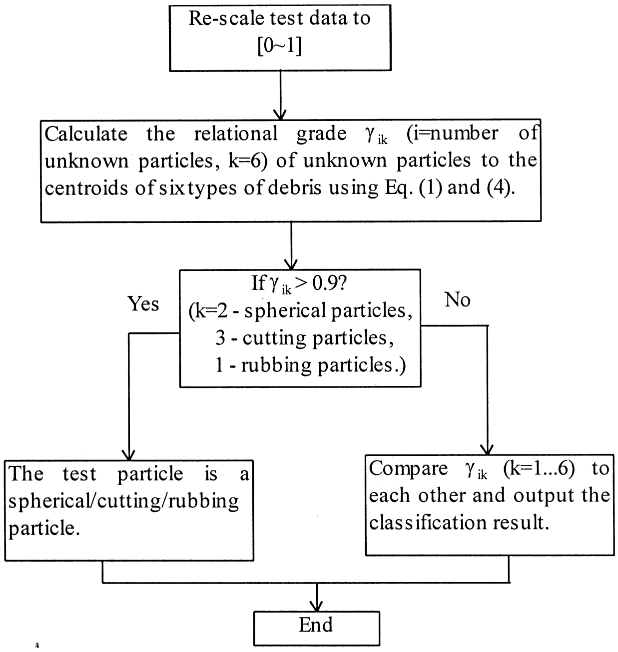

Fig. 3. Diagram of the wear particle classification system using grey relational analysis.

the membership function, which is normally applied to describing a fuzzy set [17], has been used to measure the similarities between test data and the reference data here. Fig. 2 illustrates how to determine the membership value μ of a test feature $x_i(j)$ to the reference value $x_0(j)$, where $x_i(j)$ is the jth descriptor of the ith test particle. Table 6 displays the calculating schematics of the nine parameters to the centroids of six types of wear debris.

Using the above stated method, test data are re-scaled into the interval of [0–1]. Then, the re-scaled data can be used in Eqs. (1) and (4) to calculate the relational grades.

4.4. Classification mechanism

Since rubbing, spherical and cutting debris have well-defined boundary morphologies, they can be easily identified from test particles. Therefore, the system checks if a test particle is one of these three types of debris first. If it is not, further comparison among the relational grades will be conducted to determine if the particle belongs to laminar, chunk or severe sliding particles. The flow chart of the grey relational decision is displayed in Fig. 3.

5. Test examples

Six wear particles shown in Fig. 1a–f are test examples. The classification results of these examples in the grey system are displayed in Table 7.

Table 7 has demonstrated that the particles shown in Fig. 1a–c have the relational grade of 1.0 to rubbing, cutting and spherical particles, respectively. This indicates

Table 7
The relational grades of the test particles shown in Fig. 1 to six types of wear debris

Examples	Types of wear particles (the grey relational grade)					
	Rubbing	Cutting	Spherical	Laminar	Chunk	Severe sliding
Fig. 1a	1.00	0.00	0.00	0.00	0.00	0.00
Fig. 1b	0.00	1.00	0.00	0.00	0.00	0.00
Fig. 1c	0.00	0.00	1.00	0.00	0.00	0.00
Fig. 1d	0.00	0.00	0.00	0.84	0.75	0.77
Fig. 1e	0.00	0.00	0.00	0.75	0.81	0.09
Fig. 1f	0.00	0.02	0.07	0.74	0.70	0.80

that these three particles have been identified as rubbing, cutting and spherical debris undoubtedly. Investigating these particles, the characteristics of their shape profiles in visual description reveal the same results. Therefore, the classification results in the grey system tally with that of visual inspection.

For the particles shown in Fig. 1d–f, the classification results displayed in Table 7 are not as obvious as the former ones. This may be due to the complexity of the morphologies of the laminar, chunk and severe sliding wear particle analyses [1,2]. Besides this, the difficulty of using one or two descriptors to characterise the distinguishing features of these wear particles may be another reason. Even though certain difficulties exist so far, the main characteristics of these three types of wear particles have been captured by using the descriptors shown in Table 3. Based on the parameters, Fig. 1d has been classified as a laminar particle with the relational grade of 0.84, while Fig. 1e is more likely to be a chunk particle. The grey classification system has revealed that the parti-

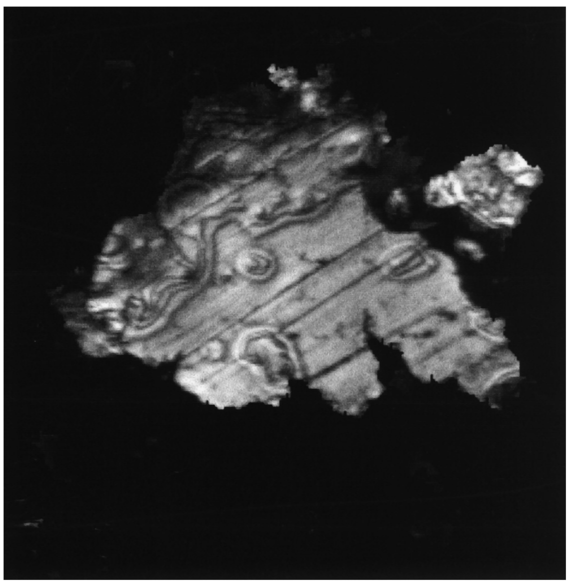

Fig. 4. An example of the wear particle which has combined features of more than one type of wear particles.

Table 8
The relational grades of the test particle shown in Fig. 4

Example	Types of wear particles (the grey relational grade)					
	Rubbing	Cutting	Spherical	Laminar	Chunk	Severe sliding
Fig. 4	0.42	0.00	0.00	0.82	0.44	0.81

cle displayed in Fig. 1f has the closest relationship with severe sliding particles than any other types. This is consistent with visual analysis.

According to this study, an unknown particle represented as x_i can be identified as the kth type if the γ_{ik} ($k = 1, 2, \ldots, 6$) is greater than or equal to 0.8. Moreover, the identification reveals the wear mechanisms and machine condition. For example, the identification of the presence of chunk particles indicates high load and/or speed of gears. Machine inspection needs to be performed as soon as possible. In some cases, more than one γ_{ik} may be less than or greater than 0.8 simultaneously. Then, it is hard to classify the particle into only one type of wear particle. The ith test particle may then belong to two or more classes depending on the relational grades.

Fig. 4 shows the image of an example for this case. The identification results are displayed in Table 8. There are two values in Table 8 which are greater than 0.8. This result reveals that the test particle is similar to both laminar and severe sliding wear particles. From visual inspection, it can be seen that this particle does have combined features of laminar and chunk particles. Furthermore, the presence of this kind of particle indicates that there is combined rolling and sliding wear in the machine. Machine monitoring needs to be conducted carefully so that the quantity and the origin of the wear particles can be further examined for locating the problem.

6. Conclusions

This study has demonstrated that the relational grade analysis of grey systems has a simple mechanism for grey relational analysis and decision making. The classification system can be easily developed and modified according to different applications. Moreover, wear debris have been successfully classified into six classes based on the relational grade—fuzzy membership.

The investigated automatic wear particle identification system has shown that it is possible to describe the distinct characteristics of wear debris and identify them using a few numerical parameters. As a result, the necessity of human experience and expertise can be significantly reduced for wear particle analysis. More work is being conducted to develop an automatic wear particle study system towards practical applications. It includes the further development of the laser scanning confocal microscope to accomplish fully automated image acquisition, and the development of an artificial intelligence system for detecting and reporting machine condition according to the results of wear particle analysis.

Acknowledgements

The authors would like to thank Mr. John Hardy from WestTrac for providing oil samples and information on machines from industry.

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