KSTLE International Journal, Vol. 2, No. 1, June 2001, pp. 35-39

A Study on Statistical Classification of Wear Debris Morphology

Unchung Cho†

MEMS Lab., Samsung Advanced Institute of Technology, Kiheung, Korea

Abstract : In this paper, statistical approach is undertaken to investigate the classification of wear debris which is the key function of objective assessment of wear debris morphology. Wear tests are run to produce various kinds of wear debris. The images of wear debris from wear tests are captured with image acquisition equipment. By thresholding, two-dimensional binary images of wear debris are made and, then, morphological parameters are used to quantify the images of debris. Parametric and nonparametric discriminant method are employed to classify wear debris into predefined wear conditions. It is demonstrated that classification accuracy of parametric and nonparametric discriminant method is similar. The selected use of morphological parameters by stepwise discriminant analysis can generally improve the classification accuracy of parametric and nonparametric discriminant method.

Key words : Wear particles, condition monitoring, condition-based maintenance, ferrography, statistical analysis

Introduction

Wear debris analysis has been a subject of practical and economical interest for many years, since it is possible to determine wear modes in a machine from observation of the debris in the lubricant without requiring access to the wear surfaces themselves [1]. Microscopic wear particles transported through oil-wetted systems are unique, having individual characteristics which bear evidence of the conditions under which they were formed. Careful examination of the quantity, size, composition, and morphology of particles can yield specific information about the operating condition of the moving surfaces of the machine elements from which they were produced.

Wear debris have been systematically classified into different wear regimes so that observed wear debris features can be correlated with possible wear situations [2]. This may be the best way in wear debris analysis, but there are few cases where one can be sure of the cause of the particular debris. Therefore, one often needs to rely solely on the appearance and from that appearance, suggest a likely source [3]. Although visual assessment of wear debris by microscopy is a useful condition monitoring technique, the use has been limited by several drawbacks. The interpretation procedure of wear debris is slower and more expensive than other methods. It is subject to individual judgment, and it requires skilled interpretation. The results are not quantitative, and may not be precisely reproduced. To overcome subjectivity, image processing techniques and numerical parameters have been applied to quantify debris morphology [4,5]. However, specific methodologies which can utilize the data of morphological parameters of wear debris for classification of wear conditions have not been developed. Development of on-line and real-time optical debris monitoring system also requires automatic classification of wear debris for an early warning of machinery failures.

This work investigates the statistical classification of wear debris morphology with respect to wearing conditions to reduce the subjectivity of optical debris monitoring. Parametric and nonparametric discriminant methods are applied to classify wear debris into wear conditions, and their classification accuracy is studied.

Experiments

Five test variables are chosen for wear tests: normal load, contact geometry, surface roughness, lubricating oil and material combination. Block-on-ring and cylinder-on-ring model tests are run to generate wear debris of different categories under various wear conditions-three different loading conditions, two different material combinations, two different types of contact geometry, two different surface roughnesses of specimen, and two different oils, as summarized in Table 1. Wear tests are designed so that a single wear variable is different in two wear tests. The sliding speed of the ring is 0.0082 m/s. Aluminum 6061 (110 DPH Vickers) and brass 360 (135 DPH Vickers) are used for the specimens of blocks and cylinders. SAE 10W engine lubricant and extra heavy mineral oil, which are chemically dissimilar, are used to lubricate contact surface. The viscosity and specific gravity of the extra heavy mineral oil are 72.76 cSt at 310 K, 78.84 cSt at 372 K and 0.8750-0.8830, respectively. The supply of lubricant is maintained by dropping oil onto a rotating ring, and the used oil that drops from the test ring by gravity is collected in a container. After wear tests, the collected oil is used to capture the images of wear debris.

†Corresponding author; Tel: 82-31-280-8044; Fax: 82-31-280-6955
E-mail: cho@sait.samsung.co.kr

Table 1. Wear test conditions

Test	Test conditions	
1	brass block (Ra: 0.04 μm)-on-steel ring (Ra: 0.08 μm)	266.9 N, SAE 10W
2	brass block (Ra: 0.04 μm)-on-steel ring (Ra: 0.08 μm)	311.4 N, SAE 10W
3	brass block (Ra: 0.04 μm)-on-steel ring (Ra: 0.08 μm)	355.9 N, SAE 10W
4	brass cylinder (Ra: 0.04 μm)-on-steel ring (Ra: 0.08 μm)	266.9 N, SAE 10W
5	brass cylinder (Ra: 0.04 μm)-on-steel ring (Ra: 0.08 μm)	311.4 N, SAE 10W
6	brass cylinder (Ra: 0.04 μm)-on-steel ring (Ra: 0.08 μm)	355.9 N, SAE 10W
7	brass block (Ra: 0.04 μm)-on-steel ring (Ra: 0.16 μm)	311.4 N, SAE 10W
8	aluminum block (Ra: 0.04 μm)-on-steel ring (Ra: 0.08 μm)	311.4 N, mineral
9	brass block (Ra: 0.04 μm)-on-steel ring (Ra: 0.08 μm)	311.4 N, mineral

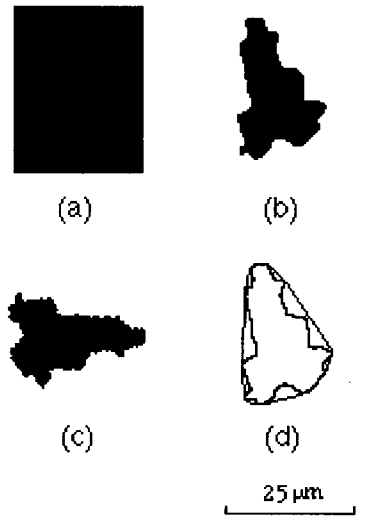

Fig. 1. Image of a wear particle with transmitted light only (a), binary image (b), rotated binary image for major and minor length measurement (c), and convex hull (d).

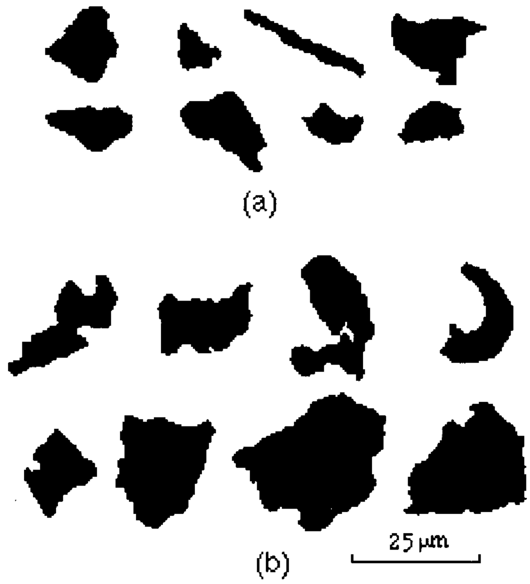

Fig. 2. Two-dimensional binary images of wear debris from wear test 1 (a) and 2 (b).

Image Processing and Quantification

Images of wear debris are captured so that debris morphology is processed by imaging techniques and quantified with numerical parameters. For two-dimensional imaging, the image acquisition equipment consists of an optical microscope, a high resolution CCD camera, a frame grabber, and an image processing and analysis program. The used oil of each wear test is mounted on a glass slide. The debris of brass and aluminum specimens are selected by color and their images are captured with both transmitted and reflected light. The morphology of wear debris is irregular and, hence, any overlapped part cannot be recovered. Wear debris are sometimes diluted in solution to separate from one another. To make thresholding easy, the image is also captured without reflected light, as shown in Fig. 1 (a). After thresholding, morphological parameters are used to quantify two-dimensional binary images of debris, as shown in Fig. 2 (b).

Morphological parameters used in this work can be classified into three categories: size, curvature, and shape, as follows:

- Size: area, perimeter, major and minor length, convex hull area, convex hull perimeter
- Curvature: standard deviation, skewness and kurtosis
- Shape: aspect ratio, roundness, roundness factor, convexity and solidity

Area and perimeter are measured by counting the number of the pixels in the binary image of wear debris and then converted to μm^2 and μm. Major length and minor length are determined using Feret's diameter, which is the maximum distance between two parallel lines, set at a fixed angle, which just touch the shape in the position it takes [3]. The angle of the maximum axis of an object is found out and the object is rotated by the angle so that the maximum axis lies horizontal, as shown in Fig. 1 (c). The major and minor length are the width and height of a rectangle box which just touch the shape. Convex hull area and convex hull perimeter are measured from a convex region is drawn by Jarvis' march [6], which generates the smallest convex region that completely encloses the target region, as shown in Fig. 1 (d). Standard deviation, skewness,

Table 2. Data sets

Data	Source of wear debris	Difference in wear conditions
1	wear test 1 + 2	normal load
2	wear test 2 + 3	normal load
3	wear test 1 + 3	normal load
4	wear test 4 + 5	normal load
5	wear test 5 + 6	normal load
6	wear test 4 + 6	normal load
7	wear test 1 + 4	contact geometry
8	wear test 2 + 5	contact geometry
9	wear test 3 + 6	contact geometry
10	wear test 2 + 7	surface roughness
11	wear test 2 + 9	oil
12	wear test 8 + 9	material

and kurtosis are calculated from the octal sequence, and these values are used to compare the curvatures of objects [4]. The shape of debris is characterized in terms of elongation and ruggedness using aspect ratio (major length/minor length), roundness (π length^2/4 area), roundness factor (π length^2/4 area), convexity (convex hull perimeter/perimeter) and solidity (area/convex hull area). Curvature analysis is applied to quantify the smoothness of debris outline. The border of debris is traced counterclockwise from pixel to pixel and movement is recorded by octal sequence which represents the relative angle of the next pixel from the last one [7]. The curvature pattern, which the octal sequence is transformed into, is characterized with standard deviation, skewness, and kurtosis [4]. In this work, debris morphology is quantified with morphological parameters except for surface texture and thickness.

Data Sets

Wear debris are collected from each wear test and their images are quantified with the 14 morphological parameters. Data sets, each of which includes the values of 14 morphological parameters for each wear debris, are made from harvested wear debris from 9 wear tests. Data 1, 2, 3, ..., 12 are made by combining two data sets from the original 9 data sets so that one test condition is different in each data set, as shown in Table 2. In the data 1, 2, 3, ..., 12, difference of wear condition is the controlling parameter which is responsible for the change of wear debris formation. Discriminant analysis is applied to classify wear debris from two different wear conditions with respect to different levels of normal load in data 1-6, contact geometry in data 7-9, surface roughness in data 10, oil in data 11 and material in data 12.

Classification

Two-dimensional binary images of wear debris in wear tests 1 and 2 are shown in Fig. 2. It can be visually recognized that the wear debris from wear tests 1 and 2 are somewhat different due to the difference in wear conditions. However, it is highly unlikely that the criteria of distinguishing wear debris from wear test 1 from those of wear test 2 can be made based on individual judgment. For objective assessment, discriminant analysis can be applied to make a discriminant classifier with which wear debris can be statistically classified into wear test 1 or 2. In this study, wear debris are sorted into previously defined wear conditions by parametric and nonparametric discriminant methods of which difference is that parametric discriminant methods depend on distributional assumptions but nonparametric discriminant methods do not. When the distributional assumptions are not satisfied or unknown, nonparametric discriminant methods are usually used. The power of the parametric discriminant methods is attenuated by the violations of the underlying assumptions, but it is hard to tell which method offers better results.

When the distribution within each group is assumed to be multivariate normal, a parametric discriminant method can be used to develop a discriminant function. The discriminant function, also known as a classification criterion, can be based on either the individual within-group covariance matrices or the pooled covariance matrix. Nonparametric discriminant methods are based on nonparametric estimates of group-specific probability densities. Either a kernel method or the k-nearest-neighbor method can be used to generate a nonparametric density estimate in each group and to produce a classification criterion. The kernel density-uniform, normal, Epanechnikov, biweight, and triweight-in the kernel method and the value of k in the k-nearest-neighbor method should be chosen according to each data. In this study, the k-nearest-neighbor method is used to generate a nonparametric density estimate in each group and to produce a classification criterion, since the optimal value of k can be available through few trial-and-error. The k-nearest-neighbor rule classifies wear debris by assigning it the label most frequently represented among the k nearest samples [7]. After several different values of k are tried for each original 9 data set, k is fixed to 3 to give the best classification accuracy.

Parametric and nonparametric discriminant analysis are performed with all the 14 morphological parameters and a subset of parameters chosen from stepwise discriminant analysis. The stepwise discriminant analysis selects the subset of parameters to produce a good discrimination model using forward selection, backward elimination, or stepwise selection. The set of variables is assumed to be multivariate normal with a common covariance matrix. The significance level of 0.15 is used for both adding variables in the forward selection mode and retaining variables in the backward elimination mode. The models selected by the stepwise discriminant analysis are not necessarily the best possible models. In the selection of variables for entry, only one variable can be entered into the model at each step. The selection process does not take into account the relationships among all the variables. Some important variables could be excluded in the process. Thus, stepwise discriminant analysis should be used in combination with knowledge of data in selecting a discrimination model. In alternative way, orthogonalization can be used to make

Table 3. Classification accuracy by parametric and nonparametric discriminant analysis with 14 morphological parameters

Data	Classification accuracy (%)	
	Parametric discriminant analysis	Nonparametric discriminant analysis
1	73.4 ± 13.5	69.9 ± 18.0
2	65.2 ± 12.2	61.5 ± 21.0
3	80.6 ± 11.2	77.2 ± 14.6
4	92.4 ± 7.4	89.9 ± 12.0
5	57.0 ± 17.6	53.4 ± 22.9
6	91.6 ± 6.4	77.2 ± 14.6
7	85.8 ± 7.7	80.1 ± 15.8
8	98.6 ± 3.1	97.2 ± 8.2
9	93.9 ± 8.6	94.3 ± 11.1
10	74.8 ± 12.0	79.9 ± 16.2
11	99.3 ± 2.0	100.0 ± 0.0
12	99.3 ± 1.6	100.0 ± 2.8

unselected variable independent from the selected ones.

Classification accuracy and standard error are calculated by jackknifing and leave-one-out crossvalidation [8,9]. When there is a sample $\{x_1, x_2, x_3, ..., x_n\}$, the jackknife technique, which is used for estimating the bias and standard error of an estimate [8], focuses on the samples that leave out one observation at a time:

$$x_{(i)} = (x_1, x_2, ..., x_{i-1}, x_{i+1}, ..., x_n) \quad (1)$$

for $i = 1,2, ..., n$, called jackknife samples. The ith jackknife sample consists of the data set with the ith observation removed. Let $q_{(i)}$ be the ith jackknife replication of q, classification accuracy. Each $q_{(i)}$ is calculated by leave-one-out cross-validation, which is performed as follows:

(a) Split the data into n-1(total number of sample after jackknifing) parts.
(b) For the kth part, calculate classification accuracy, q_i^k using the other n-2 parts as the training set and use kth part as the test set.
(c) Do the above for k = 1,2, ..., n-1.

Based on the above procedure,

$$q_{(i)} = \frac{1}{n-1}\sum_{k=1}^{n-1} q_i^k . \quad (2)$$

The jackknife estimate of standard error is defined by

$$SE_{jack} = \sqrt{\frac{n-1}{n}\sum_{i=1}^{n}(q_{(i)} - q_{(.)})^2}, \quad (3)$$

where

$$q(.) = \frac{1}{n}\sum_{i=1}^{n} q_{(i)} .$$

Given an estimate classification accuracy q and an estimated standard error SEjack, the usual 90% confidence interval for q is

$$q \pm 1.645 SE_{jack} \quad (4)$$

where 1.645 comes from a standard normal table.

Table 4. The subset of morphological parameters selected by stepwise discriminant analysis: AR=area, PE=perimeter, MA=major length, MI=minor length, HA=convex hull area, HP=convex hull perimeter, ST=standard deviation, SK=skewness, KU=kurtosis, AS=aspect ratio, RF=roundness factor, RO=roundness, CO=convexity, SO=solidity

Effect	Data	Morphological parameters													
		size					curvature				shape				
		AR	PE	MA	MI	HA	HP	ST	SK	KU	AR	RF	RO	CO	SO
load	1	*	*	*				*	*	*	*	*	*	*	*
	2		*	*		*		*	*		*	*	*	*	
	3	*	*	*		*	*	*	*		*	*	*		*
	4	*		*			*	*	*				*		
	5	*		*			*	*	*	*					
	6	*	*	*	*		*	*	*		*	*	*	*	*
contact geometry	7	*	*	*					*	*		*	*	*	
	8						*	*	*	*	*				
	9	*					*	*	*				*		
surface roughness	10		*	*		*		*	*		*	*	*	*	
oil	11	*						*	*	*	*			*	
material	12	*		*	*			*	*	*	*				

Table 5. Classification accuracy by parametric and nonparametric discriminant analysis with the subset of morphological parameters selected by stepwise discriminant analysis

Data	Classification accuracy (%)	
	Parametric discriminant analysis	Nonparametric discriminant analysis
1	74.7 ± 7.8	77.3 ± 12.6
2	65.7 ± 17.3	62.8 ± 16.0
3	83.4 ± 9.1	83.0 ± 9.9
4	89.6 ± 8.9	93.5 ± 8.0
5	61.7 ± 11.0	59.1 ± 14.2
6	92.3 ± 6.7	92.3 ± 5.8
7	87.2 ± 5.8	83.2 ± 11.4
8	98.6 ± 2.0	99.4 ± 5.4
9	95.0 ± 4.6	96.5 ± 4.0
10	74.5 ± 6.6	75.3 ± 11.4
11	99.3 ± 1.2	100.0 ± 0.0
12	99.3 ± 1.2	100.0 ± 1.2

With the 14 morphological parameters, the classification accuracy of parametric and nonparametric discriminant analysis is similar, as shown in Table 3. Stepwise discriminant method is applied to select a subset of morphological parameters, as presented in Table 4. When the subset of morphological parameters is used, the classification accuracy of both parametric and nonparametric discriminant method is generally slightly improved, as shown in Table 5.

Conclusions

It is demonstrated that wear debris of different categories can be statistically classified according to wear conditions without subjective individual judgment. Wear debris are generated under various test conditions and their two-dimensional binary images are quantified with 14 morphological parameters. Discriminant analysis is employed to classify wear debris based on the morphological parameters of two-dimensional binary images of debris morphology. The classification accuracy of discriminant methods is summarized as follows:

(1) The classification accuracy of all discriminant analysis is good enough to classify wear debris into wear conditions using two-dimensional binary images of wear debris.
(2) The classification accuracy of parametric and nonparametric discriminant method is similar with respect to both the 14 morphological parameters and the subset of morphological parameters selected by stepwise discriminant analysis.
(3) The classification accuracy of parametric and nonparametric discriminant method is generally improved for the subset of morphological parameters selected by stepwise discriminant analysis compared with the 14 morphological parameters.

References

1. Reda, A. A., Bowen, R. and Westcott, V. C., Characteristics of particles generated at the interface between sliding steel surfaces, Wear, Vol. 34, 1975, pp. 261-273.
2. Anderson, D. W., Wear Particle Atlas (Revised), Naval Air Eng. Center Report No. NAEC-92-163 (1982).
3. Hunt, T. M., Handbook of wear debris analysis and particle detection in liquids, Elsevier Applied Science, 1993.
4. Thomas, A. D. H., Davies, T. and Luxmoore, A. R., Computer image analysis for indentation of wear particles, Wear, 142 (1991), pp. 213-226.
5. Kirk, T. B., Panzera, D., Anamalay, R. V. and Xu, Z. L., Computer image analysis of wear debris for machine condition monitoring and fault diagnosis, Wear, Vol. 181-183 (1995), pp. 717-722.
6. Parker, J. R., Practical computer vision using C, Wiley, 1993.
7. Duda, R. O. and Hart, P. E., Pattern classification and scene analysis, John Wiley & Sons, 1973.
8. Efron, B. and Tibshirani, R. J., An introduction to the Bootstrap, Chapman & Hall, 1993.
9. Mosteller, F. and Tukey, J. W., Data analysis and regression, Addison-Wesley Publishing Company, 1977.