Wear 392–393 (2017) 152–158

Contents lists available at ScienceDirect

Wear

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

A hybrid search-tree discriminant technique for multivariate wear debris classification

Yeping Peng[a], Tonghai Wu[b], Guangzhong Cao[a,*], Sudan Huang[a], Hongkun Wu[c], Ngaiming Kwok[c], Zhongxiao Peng[c]

[a] Shenzhen Key Laboratory of Electromagnetic Control, College of Mechatronics and Control Engineering, Shenzhen University, Shenzhen 518060, China
[b] Key Laboratory of Education Ministry for Modern Design and Rotor-Bearing System, School of Mechanical Engineering, Xi'an Jiaotong University, Xi'an 710049, China
[c] School of Mechanical and Manufacturing Engineering, The University of New South Wales, Sydney, NSW 2052, Australia

ARTICLE INFO

Keywords:
Wear debris analysis
Wear particle classification
Search-tree discriminant technique
Intelligent recognition
Online condition monitoring

ABSTRACT

Wear debris analysis (WDA) is an effective machine health monitoring technique in which wear debris attributes can reveal wear mechanisms and particle colours can be used to detect oxidation. However, most of the existing approaches to WDA are based on analytical ferrography. Online wear debris typing is still difficult to achieve because of the low resolution of online particle images. In this work, a hybrid search-tree discriminant technique is described. It permits identification of online wear particles by combining their colour attributes and multi-view particle features. A multi-class support vector data description multi-SVDD, the K-means and a support vector machine SVM are integrated to establish a three-level search-tree model to discriminate multivariate wear debris including red and black oxides, cutting, spherical, fatigue and sliding particles. First, the oxides are identified based on their special colour information using the multi-SVDD. Second, the K-means is used to look for the clustering centres of cutting and spherical particles by utilizing their distinct features of aspect ratio and sphericity. The third level built by SVM is adopted to distinguish fatigue and sliding particles based on their height aspect ratio and height-to-width aspect ratio. Experiments have demonstrated that the search-tree discrimination model is effective for multivariate wear debris classification. The proposed method provides a solution to the existing problems in online wear particle identification for wear mechanism analysis.

1. Introduction

Condition based maintenance (CBM) is an important research topic of machine condition monitoring, which has great potential benefits and savings by reducing maintenance cost, limiting machinery damage and avoiding production loss [1]. Therefore, various CBM techniques have been investigated, including vibration analysis, acoustic emission, oil analysis and (wear debris analysis WDA) [2–5]. In particular, wear debris carries useful information about machine wear status. This methodology has been recognised as one of the most effective methods of CBM [6]. However, to accurately reflect machine health conditions, a large amount of wear particles need to be collected, examined and identified based on their morphological and compositional attributes [7].

The WDA technique has been extensively explored to identify machine failure modes in terms of wear particle size, shape and material characteristics. Attempts of wear particle classification using image processing techniques have been made to assess wear mechanisms [8]. Correspondingly, various automated classifying tools have been developed for wear debris identification so that a more objective, efficient and consistent approach can be used to replace the manual classification which often relies on experience and can be subjective, labour intensive and tedious. For example, the computer aided vision engineering CAVE system employs Fourier, curvature and/or fractals techniques to extract the shape, edge and surface details to characterize wear particles and classify them using a neural network [9]. However, the CAVE system was not adopted in practice due to its complexity. In addition, standard image processing techniques used in the CAVE have difficulties in separating overlapping particles in poor-quality images. In order to deal with the above issues, CAVE was further developed as a new classifier, that is, the systematic classification of oil-wetted particles SYCLOPS [10]. The system was used in detecting early failure in helicopter gearboxes. The particle characteristics were manually selected and fed to the SYCLOPS for wear debris classification, in which process, human input was needed. Also, the CAVE and SYCLOPS systems both depended on wear debris features extracted from two-

* Corresponding author.
E-mail address: gzcao@szu.edu.cn (G. Cao).

http://dx.doi.org/10.1016/j.wear.2017.09.022
Received 17 August 2017; Received in revised form 23 September 2017; Accepted 25 September 2017
Available online 28 September 2017

dimensional images.

It is known that three-dimensional (3D) features, in particular, the thickness information, are very useful for identifying wear particles which have similar features on their dominant surfaces but different heights (thicknesses). Therefore, stereo scanning electron microscopy SEM, laser scanning con-3 focal microscopy LSCM and atomic force microscopy AFM are applied to obtain 3D features including high resolution surface information and the thickness of wear debris [11–13]. Based on this, cutting, fatigue and spherical wear particles were identified using a fuzzy grey system or an expert system [14,15]. Moreover, fatigue and severe sliding wear particles can be distinguished based on their surface and texture information [16]. Thus, offline WDA is widely used to infer wear mechanisms through wear particle classification.

For the purpose of wear mechanism assessment, online wear particle classification methods are investigated. With online oil and wear debris monitoring, an online visual ferrograph OLVF sensor was developed to capture wear particles in online condition monitoring [17]. By utilizing the colour information, copper, iron and aluminium particles were identified [18]. An online wear particle classification model was also established using a neural network to distinguish normal, cutting, fatigue and severe sliding wear debris [19]. However, individual particles were not easily available because images of overlapping particles were commonly captured with OLVF. Hence, online wear debris recognition still remains as a main challenge. To overcome the drawback of particle overlap, a LaserNet Fines LNF system was developed [20]. A laser imaging-based flow-free cell was designed to capture wear particles suspended in lubricating oil, making it possible to measure the particle size and shape features. A neural network was then used to classify the types of wear debris. However, black-and-white laser images captured by the LNF cannot provide colour and have limited surface information [21]. In addition, as found in other existing systems, two-dimensional (2D) particle images were captured without 3D morphological information such as thickness, making the identification of certain types of wear debris difficult or infeasible.

In order to further develop wear mechanism analysis capability, the accuracy of online particle classification needs to be improved. To achieve this goal, an online recognition method is proposed to classify multivariate wear particles including oxides, cutting, spherical, fatigue and sliding wear debris. Due to the difficulties in online characterization of different types of wear particles, an identification model is established based on integrated feature information and a search-tree multivariate discriminant analysis technique. The target particles are divided into three groups, that is, red-black oxides, cutting-spherical particles and fatigue-sliding particles. The colour and 3D morphological features of wear debris are used for particle classification. A multi-SVDD, a K-means clustering algorithm and a SVM are integrated into a three-level search-tree discrimination model for particle classification. The performance of the proposed identification method is evaluated using more than 200 wear particle samples.

The rest of this paper is organised as follows. The characteristics of online wear particles are reviewed in Section 2. The search-tree discrimination technique based particle classification method is detailed in Section 3. Experiments are described and the discussion of results is presented in Section 4. Finally, conclusions are drawn in Section 5.

2. Characteristics of online wear particles

Images of six typical wear debris, namely, red and black oxides, cutting, spherical, fatigue and sliding particles, were captured using an analytical ferrograph and a dynamic particle imaging system (DPIS) [22] and they are shown in Fig. 1(a) and (b) respectively. It can be seen that the ferrograph images are able to show the contour and surface details of the particles. In contrast, only fuzzy contour and surface information of the online wear particles are obtained. The poor image quality may result in low accuracy of online particle identification. For instance, fatigue and sliding particles are hard to be distinguished when they have similar size and shape features, as shown in Fig. 1. Offline ferrograph analysis provides shape and texture features to identify the two types of wear debris. However, it is not feasible to extract the surface details of wear debris from fuzzy images, as shown in Fig. 1(b). This is the reason why detecting faults of fatigue and sliding particles identification is often conducted in a multi-class classifier established by a neural network and/or an expert system [23]. Due to the poor quality of online particle images, it is necessary that appropriate intelligent algorithms are developed according to the particle properties for multivariate debris classification.

Firstly, in terms of the characteristic attributes of the above six wear particle types, oxides can be detected using their distinctive colour information. Secondly, compared to other particles, the cutting and spherical particles have their own characteristic features, aspect ratio (*AR*) and sphericity (*S*) respectively. The last two particle types, fatigue and sliding particles, are difficult to be distinguished due to their similar shape features as mentioned above. On the other hand, these two types of particles have differences in their heights (i.e., thickness), as shown in Fig. 2.

In general, the height aspect ratio (*HAR*) and the height to width aspect ratio (*HWAR*) of sliding particles are higher than those of fatigue debris [6]. Based on this, online recognition of fatigue and sliding particles can be achieved. Finally, all five types of particles are divided into three groups, 'red-black oxides', 'cutting-spherical particles', and 'fatigue-sliding particles', according to the identification sequence. The colour and the geometric features quantified using *AR*, *S*, *HAR* and *HWAR* are employed in this classification process, as shown in Fig. 3. The development of a wear particle classification method for identifying six wear debris types into three groups is presented in the next section.

3. A hybrid search-tree discrimination model for multivariate debris classification

In order to improve the accuracy of online wear particle recognition, a three-level search-tree discrimination model for six kinds of wear particles classification is established by combining three intelligent algorithms of multi-SVDD, K-means and SVM. An illustration of the search-tree discrimination method is shown in Fig. 4. It can be seen that all wear debris samples include oxides and non-oxides, which can be divided into cutting, spherical, fatigue and sliding particles. It also can be found that the cutting, spherical, fatigue and sliding particles are recognised using two classification algorithms including K-means and SVM based on their 2D and 3D shape features. Whereas, the oxides can be identified only based on their special colour information using the multi-SVDD classifier. Therefore, the oxides should be firstly identified to make the search-tree structure be simpler. The multi-SVDD is developed to discriminate the oxides due to the fact that it is an unsupervised clustering algorithm and can obtain a satisfactory training result with only a few samples [24]. The second level of the hybrid model is to identify cutting particles with a long, curved shape and the sphere-like particles (spherical particles) using *AR* and *S*. A clustering algorithm of K-means is employed to automatically classify a large number of wear debris data to look for their cluster centres as their recognised criteria. Finally, a binary classification algorithm, SVM, is applied to distinguish fatigue chunks and severe sliding particles using *HAR* and *HWAR*. The principles of above three classification algorithms are described in the following subsections.

It needs to be mentioned that the *HAR* and *HWAR* are numerical parameters to describe particle features at different views. Therefore, the proposed classification model is aimed at the analysis of wear debris whose thickness information is available. However, the contour of online wear debris captured under dynamic particle imaging conditions is generally fuzzy, making the shape features of small particles indistinguishable. Hence, this work is focused on detecting wear particles whose major dimensions are larger than 40 μm according to the image

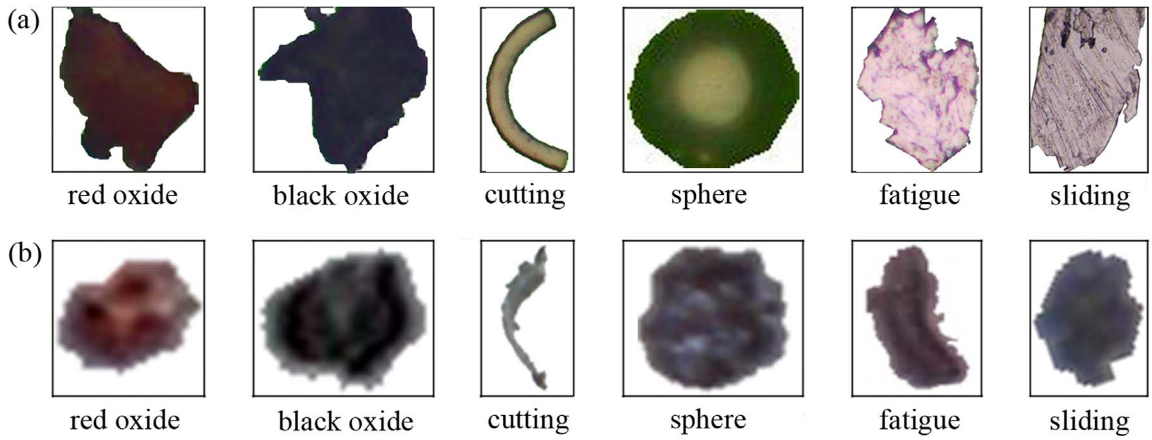

Fig. 1. Typical wear debris images captured by an analytical ferrography and the DPIS respectively: (a) ferrograph images and (b) online particle images. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)

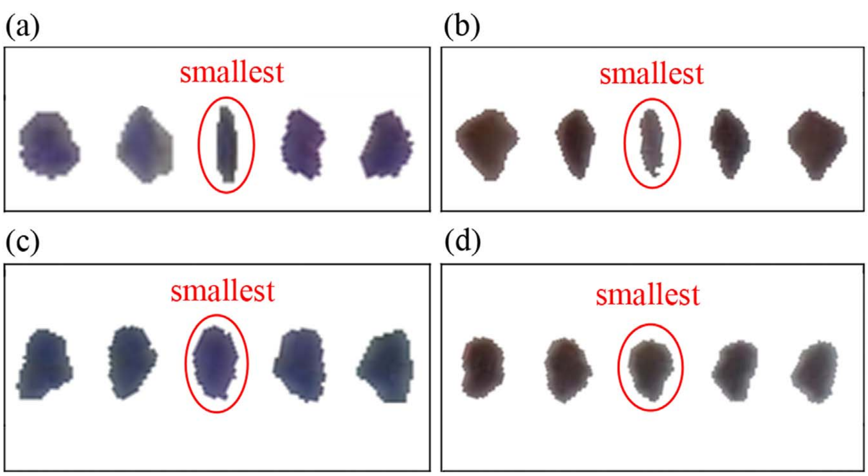

Fig. 2. Different viewing images of the fatigue and sliding wear debris: (a) sliding particle #1, (b) sliding particle #2, (c) fatigue particle #1, and (d) fatigue particle #2.

resolution and pilot experience.

3.1. Multi-class classifier established by support vector data description (multi-SVDD)

Multi-SVDD is the refinement of support vector data description SVDD which is a binary classification algorithm. The SVDD aims to look for a closed space, super-sphere, to contain all the same type of data [25]. That means a central point (o) and a radius (R) need to be confirmed.

Suppose that samples x_i, $i = 1, 2, \ldots, N$, N is the sample number, is contained in a super-sphere. Thus, the following constraint condition is imposed,

$$\|x_i - o\| \le R. \tag{1}$$

However, the practical samples are distributed unevenly. The radius may be too large if all samples are enclosed in the super-sphere. To avoid this problem, a relaxation factor (ξ) is applied to adjust the super-sphere boundary. Then the constraint condition is modified as

$$\|x_i - o\|^2 \le R^2 + \xi^2, \quad \forall\ i,\ \xi_i > 0, \tag{2}$$

and it needs to meet the minimum requirement

$$\min \left[R^2 + C \sum_i \xi_i \right], \tag{3}$$

where C is a coefficient. Eq. (2) can be optimized using the Lagrangian multiplier method, that is,

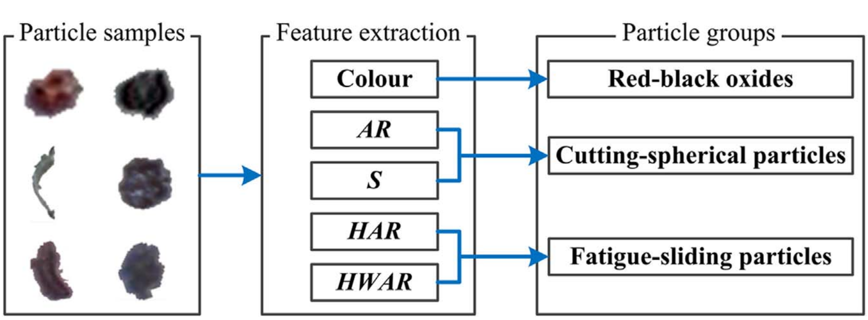

Fig. 3. Systematic diagram of wear particle classification method proposed in this work.

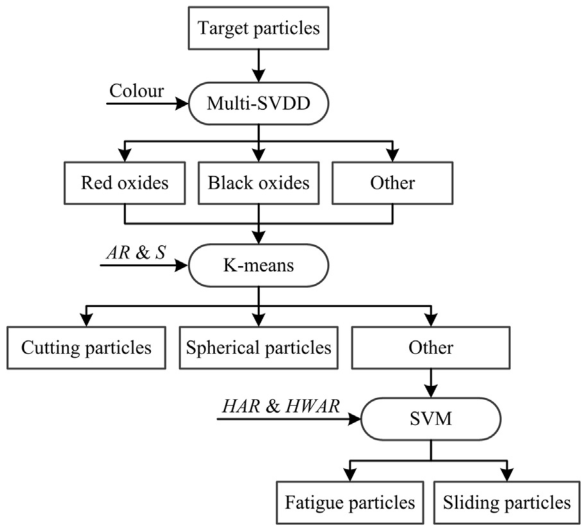

Fig. 4. A hybrid search-tree discrimination model for multi-variable particles classification.

$$L(R, o, \alpha, \xi) = R^2 + C\sum_{i=1}^{N}\xi_i - \sum_{i=1}^{N}\alpha_i[R^2 + \xi_i - (x_i^2 - 2ox_i + o^2)] - \sum_{i=1}^{N}\gamma_i\xi_i, \tag{4}$$

where, α and γ are both Lagrangian coefficients, and $\alpha_i \geq 0$, $\gamma_i \geq 0$.

In order to acquire the minimum radius, the $L(R, o, \alpha, \xi)$ should be minimum. Then we have

$$L(R, o, \alpha, \xi) = \sum_{i,j=1}^{N}\alpha_i(x_ix_j) - \sum_{i,j=1}^{N}\alpha_i\alpha_j(x_ix_j). \tag{5}$$

The samples are regarded as support vectors when they satisfy Eq. (5) and $\alpha_i \neq 0$. A new captured sample (z) can be regarded as the target object of a super-sphere if the distance between it and the central point o is less than the radius R. Hence, an identification model of the target samples is established as

$$z^2 - 2\sum_{i=1}^{N}\alpha_i(zx_i) + \sum_{i,j=1}^{N}\alpha_i\alpha_j(x_ix_j) \leq R^2. \tag{6}$$

In order to separate red and black oxides from other wear debris, every subclass of the SVDD needs to be further divided to build a multi-class classifier, that is, multi-SVDD, as shown in Fig. 5. Three different types of objects are displayed in the figure. Points a_1, a_2 and a_3 are their clustering centres; lengths R_1, R_2 and R_3 are the super-sphere radii. More details about red-black oxide wear debris identification using multi-SVDD can be found in [26].

3.2. K-means clustering algorithm

The principle of K-means based recognition modelling can be described in the following [27].

(1) The particle data is set as $x_1, x_2, \ldots, x_m$ where m is the number of samples.
(2) The collection of k samples are randomly selected as initial clustering centres, $c_1, c_2, \ldots, c_k \in \mathbb{R}$..
(3) The distances between the debris samples and the k centres are calculated. If a distance is the minimum, particle-i and the centre sample-j are regarded as in the same cluster. All the particles are divided into k groups. The shortest distance (D_i) is computed as

$$D_i = \|x_i - c_j\|, \quad i \neq j, \tag{7}$$

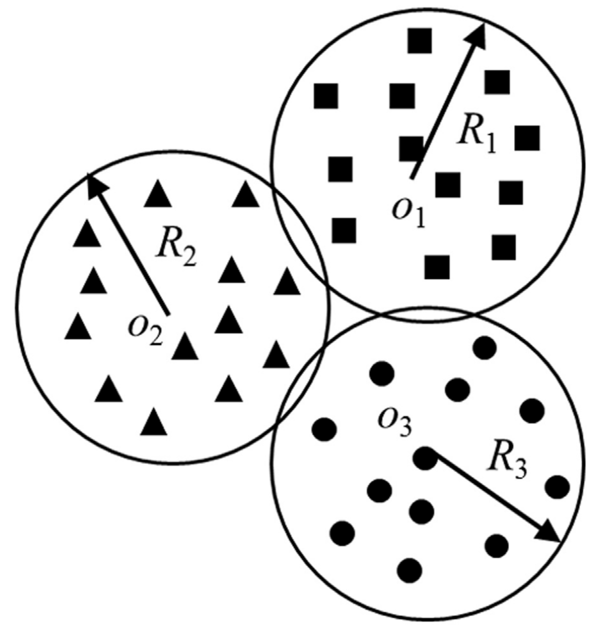

Fig. 5. Clustering results of the multi-SVDD.

where $i = 1, 2, \ldots, m_i$ and $j = 1, 2, \ldots, m_j$.

(4) The sample mean values of all clusters are calculated and set as new centres c_j', which is

$$c_j' = \frac{1}{m}\sum_{i=1}^{m_j} x_i^j, \tag{8}$$

where m_j and x_i^j are the number of samples and the objects in the j-th cluster respectively.

(5) Steps (3) and (4) are iteratively implemented. The computations stop when the new centres c_j' are close to the previous c_j, which can be expressed as

$$|c_j' - c_j| = \epsilon, \tag{9}$$

where ϵ is a threshold determined from pilot experiments.

The clustering centres can be obtained after the above iterative operations, and an example of particle clustering result is shown in Fig. 6. The centre points of different debris bunch are labelled with symbol ⊗. An optimal criterion, the shortest distance between a new captured sample and the centres, is used to decide which class the particle belongs to.

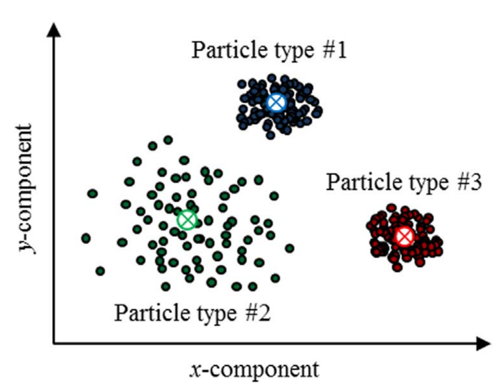

Fig. 6. An example of particle clustering using the K-means algorithm.

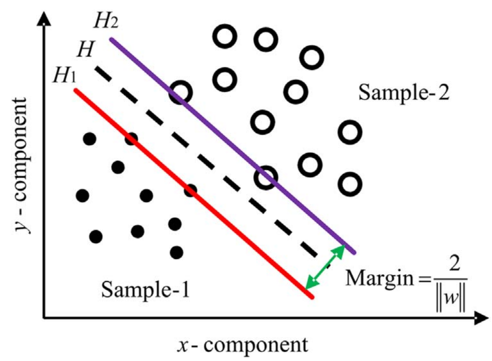

Fig. 7. An example of particle classification result using the SVM algorithm.

3.3. Support vector machine (SVM)

SVM is suitable for non-linear and high dimensional pattern recognition only using small samples, and has been widely employed in face recognition, gene classification and time series prediction [28–30]. In particular, the SVM has remarkable robust performance and its simple structure and high calculation speed meet the requirements of online wear particle classification. Fig. 7 shows two types of particle samples, and the two particle sets are separated by the line H. Lines H_1 and H_2 are parallel to line H. The SVM algorithm aims to look for the optimum line H to make the distance (Margin) between lines H_1 and H_2 be the maximum [31], which can be described as below.

Assume that the samples are expressed by $(x_h,\ y_h)$, $h = 1,\ 2,\ \ldots,\ q$, and q is the number of samples. The equation of line H is

$$y_h(wx_h + b) - 1 \geq 0. \tag{10}$$

where w is a coefficient and b is a constant. Hence, the Margin can be calculated by

$$\text{Margin} = \frac{2}{\| w \|}. \tag{11}$$

If a line satisfies Eq. (11) and the value of $\| w \|$ is the minimum, the Margin of the line to its parallel lines is the maximum accordingly [31].

4. Testing results and discussion

In order to evaluate the performance of the development, the hybrid search-tree classification model was trained using 200 classified particles. Afterwards, 30 particle samples, as shown in Fig. 8, were used to verify the effectiveness of the trained model. In order to display the debris clearer, two views of each particle including front and side views are provided.

The feature parameters, hue (H) and intensity (I) of colour components, and AR, S, HAR and $HWAR$ of the particles were extracted and are shown in Table 1. The colour information was extracted from the front view images. To verify the effectiveness of the hybrid sear-tree discrimination model, the features in Table 1 were used as the testing data, and the classification results are as follows.

The first step was to identify oxide wear debris. As shown in Table 1, the red and black oxides have their own special properties compared with other wear debris. The red and black oxides both have small intensity values which are in the range of [20, 90]. Moreover, the H component [0, 75] of the red oxides is the smallest among the others. Therefore, the H and I components were used as the input to multi-SVDD, the red and black oxides were identified sequentially, and the result is shown in Fig. 9. The testing result shows that 12 particles were identified as red oxides. However, only 8 samples (particles 4, 6, 17, 26–30) can be sure to be red oxides based on visual observation. In fact, the error of oxide identification is unavoidable because the particle colours are in non-uniform distribution. To improve the classification accuracy, image quality and feature extraction algorithm should be further developed.

It also can be found in Fig. 9 that all the wear debris samples including oxides and non-oxides can be further identified into cutting, fatigue and sliding particles. That is the reason why the oxides should be firstly identified. As shown in Fig. 4, cutting and spherical particles should be detected in the next search-tree level. However, the spherical particles are not provided to test the proposed classification model. This is because the spherical particles generated from the rolling bearings in our experiments are generally less than 40 μm, and thus they cannot be used as the target objects. Therefore, only cutting particles were clustered by the K-means algorithm. The features of AR and S in Table 1 were the input of K-means, and the sample groups were set to three. The particle clustering result is shown in Fig. 10, and the clustering centres were marked with symbol ⊗. It can be seen that the cutting particles were correctly classified.

It can also be observed in Fig. 10 that some sliding particles were mis-classified as fatigue debris. Therefore the third search-tree level is built to differentiate between fatigue and sliding particles. As mentioned before, two parameters, HAR and $HWAR$ which are able to describe multi-view features, are employed to characterize the different contour features of the two types of wear debris due to the fact that sliding particles have a smaller thickness. The identification of fatigue and sliding particles was carried out using the SVM classification algorithm, and the result is shown in Fig. 11. This indicates that the problem to distinguish fatigue debris from sliding particles can be solved rapidly by capturing dynamic morphological features.

As a result, the proposed three-level search-tree discrimination model was tested using particle colour and shape features which were selected according to their distinctive properties. Three particle groups including ‘red-black oxides’, ‘cutting-spherical particles’ and ‘fatigue-sliding particles’ were automatically classified sequentially based on multi-SVDD, K-means and SVM respectively. However, it should be mentioned that satisfactory testing results depend on the fact that the particle samples were manually selected. Hence, a higher error rate may be caused by inaccurate online feature extraction as compared to offline analysis. For instance, the problem of fatigue and sliding wear debris discrimination still remains if the exact thickness cannot be obtained [32]. In addition, laminar particles are not considered as the target objects of the current hybrid classification model. It seems that laminar and sliding particles captured in online conditions are similar in shape and thickness features, and their texture information is hard to acquire from fuzzy images.

Therefore, more work needs to be done to improve the particle identification accuracy in the future. First, the particle imaging technique should be developed to improve the image quality of small wear debris and the accuracy of feature extraction. In this case, analytical ferrograph techniques may be adapted for online analysis. Second, the clustering model should be further refined by combining colour, size, shape and contour information so that more particle types including spherical, rubbing and laminar particles can be identified. More classification algorithms have to be investigated to establish a more suitable classifier for online wear debris recognition. Furthermore, more particle samples need to be captured and trained with the established recognition model to improve the recognition accuracy.

5. Conclusions

A hybrid search-tree discriminant analysis technique was proposed for multivariate wear debris identification. The following conclusions can be drawn.

(1) A hybrid search-tree discrimination model was established by combining the multi-SVDD, K-means and SVM algorithms to identify multivariate wear particles including red-black oxides, cutting, fatigue and sliding debris.

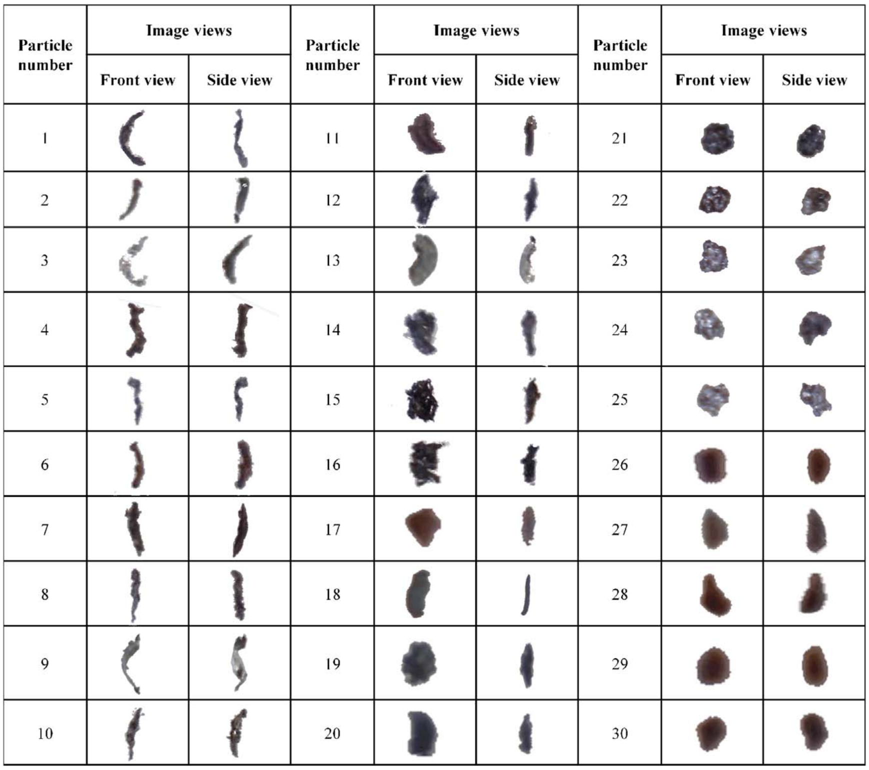

Fig. 8. A portion of wear debris samples for classification tests.

Table 1
Feature extraction results of the wear particles in Fig. 8.

Particle number	*H*	*I*	*AR*	*S*	*HAR*	*HWAR*
1	136.43	57.00	5.41	0.27	9.52	5.41
2	52.66	91.33	4.06	0.35	5.65	4.06
3	43.57	156.33	5.32	0.31	6.35	5.32
4	0.00	51.67	4.62	0.33	5.90	4.62
5	120.00	103.00	3.84	0.40	4.18	3.84
6	12.75	74.33	3.71	0.41	4.00	3.71
7	321.79	58.67	3.39	0.39	5.03	3.39
8	180.00	91.00	4.82	0.34	5.13	4.82
9	50.57	152.67	5.02	0.28	9.36	5.02
10	21.79	87.00	5.19	0.31	6.19	5.19
11	300.00	55.00	1.94	0.47	5.08	1.94
12	139.65	43.33	1.88	0.49	4.53	1.88
13	141.79	104.00	2.37	0.42	5.73	2.37
14	135.18	56.33	1.43	0.55	4.17	1.43
15	180.00	27.00	1.26	0.62	3.38	1.26
16	64.41	56.33	1.71	0.58	2.98	1.71
17	12.75	49.33	1.09	0.67	3.03	1.09
18	52.66	78.67	2.14	0.37	9.27	2.14
19	141.79	56.00	1.25	0.62	3.39	1.25
20	92.20	48.67	1.55	0.55	3.97	1.55
21	209.41	66.33	1.06	0.91	1.23	1.06
22	315.18	66.00	1.13	0.88	1.29	1.13
23	208.78	109.33	1.05	0.87	1.47	1.05
24	170.57	131.67	1.26	0.85	1.28	1.26
25	136.43	108.00	1.13	0.90	1.24	1.13
26	2.58	73.33	1.23	0.81	1.55	1.23
27	36.29	85.67	1.43	0.69	2.16	1.43
28	15.57	42.67	1.62	0.68	1.95	1.62
29	23.03	54.33	1.07	0.87	1.43	1.07
30	13.17	42.00	1.32	0.82	1.37	1.32

(2) Colour-based automatic classification of oxide wear debris was achieved by utilizing the multi-SVDD classifier. However, there is a lower bound on the error due to the fuzzy colour information and its discrete distribution.
(3) The discrimination property of cutting particles, due to a long thin shape, had made them easier to be recognised. Thus, aspect ratio

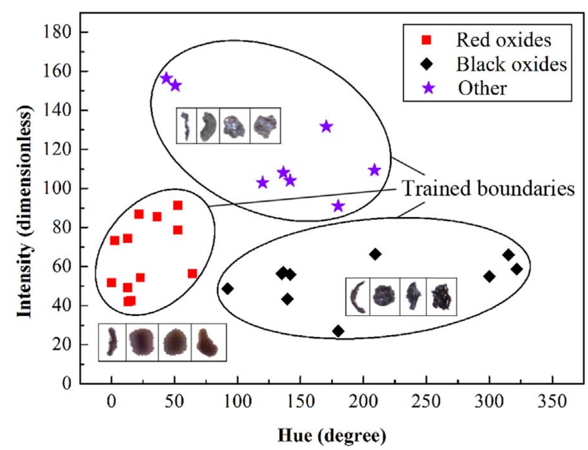

Fig. 9. The result of oxide particles identification using SVDD.

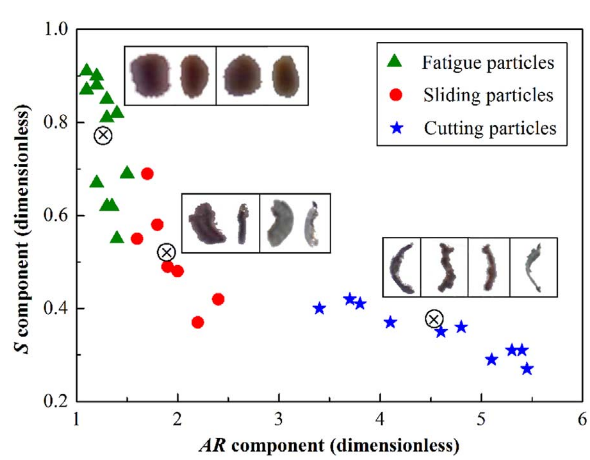

Fig. 10. The particle clustering result based on K-means.

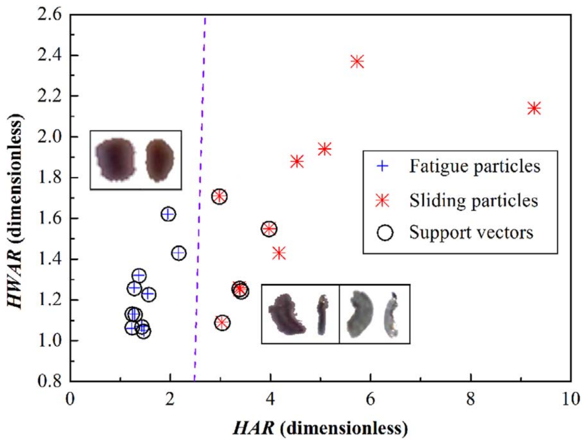

Fig. 11. The discrimination result of fatigue and sliding particles using SVM.

and sphericity were used as the criteria and the K-means, an unsupervised clustering algorithm, was applied to cluster them from other types of particles.

(4) It was verified that *HAR* and *HWAR* parameters were effective in distinguishing the sliding particles from the fatigue ones. Based on this, the SVM was employed to build a binary classifier.

(5) Future work may be directed towards combining more particle features, collecting more particle samples and optimizing automatic classification algorithms to address online wear debris identification problems like spherical and laminar particles recognition.

Acknowledgments

The authors thank the Natural Science Foundation of China, China (Grant Nos. 51677120 and 51675403) and the Natural Science Foundation of Shenzhen University, China (Grant No. 2017032).

References

[1] P. Mehta, A. Werner, L. Mears, Condition based maintenance-systems integration and intelligence using Bayesian classification and sensor fusion, J. Intell. Manuf. 26 (2015) 331–346.
[2] Z.X. Li, X.P. Yan, X.P. Wang, Z. Peng, Detection of gear cracks in a complex gearbox of wind turbines using supervised bounded component analysis of vibration signals collected from multi-channel sensors, J. Sound Vib. 371 (2016) 406–433.
[3] K. Zhang, Q.F. Meng, T. Geng, N. Wang, Ultrasonic measurement of lubricant film thickness in sliding bearings with overlapped echoes, Tribol. Int. 88 (2015) 89–94.
[4] W. Cao, G.N. Dong, W. Chen, J.Y. Wu, Y.B. Xie, Multisensor information integration for online wear condition monitoring of diesel engines, Tribol. Int. 82 (2015) 68–77.
[5] M. Soleimani, M. Sophocleous, L. Wang, J. Atkinson, I.L. Hosier, A.S. Vaughan, R.I. Taylor, R.J.K. Wood, Base oil oxidation detection using novel chemical sensors and impedance spectroscopy measurements, Sens. Actuators B: Chem. 199 (2014) 247–258.
[6] Y.P. Peng, T.H. Wu, S. Wang, Z. Peng, Wear state identification using dynamic features of wear debris for on-line purpose, Wear 376–377 (2017) 1885–1891.
[7] P.Q. Bao, S.L. Ko, Improvement of particle classification using particle expert system in automotive production, Int. J. Adv. Manuf. Technol. 87 (2016) 1443–1455.
[8] J.Q. Wang, X.L. Wang, A wear particle identification method by combining principal component analysis and grey relational analysis, Wear 304 (2013) 96–102.
[9] Q. Li, T.T. Zhao, L.C. Zhang, W.H. Sun, X. Zhao, Ferrography wear particles image recognition based on extreme learning machine, J. Electr. Comput. Eng. 2017 (2017) 1–6.
[10] T.P. Sperring, T.J. Nowell, SYCLOPSa qualitative debris classification system developed for RAF early failure detection centres, Tribol. Int. 38 (2005) 898–903.
[11] G.P. Stachowiak, G.W. Stachowiak, P. Podsiadlo, Automated classification of wear particles based on their surface texture and shape features, Tribol. Int. 41 (2008) 34–43.
[12] Z. Peng, S. Tomovich, The development of a new image acquisition & analysis system for 3D surface measurements using confocal laser scanning microscopy, Adv. Mater. Res. 32 (2008) 173–179.
[13] M.L. Wang, Z. Peng, K. Vasilev, N. Ketheesan, Investigation of wear particles generated in human knee joints using atomic force microscopy, Tribol. Lett. 51 (2013) 161–170.
[14] Z. Peng, T.B. Kirk, Wear particle classification in a fuzzy grey system, Wear 225–229 (1999) 1238–1247.
[15] Z. Peng, S. Goodwin, Wear-debris analysis in expert systems, Tribol. Lett. 11 (2001) 177–184.
[16] G.P. Stachowiak, G.W. Stachowiak, P. Podsiadlo, Automated classification of wear particles based on their surface texture and shape features, Tribol. Int. 41 (2008) 34–43.
[17] T.H. Wu, H.K. Wu, Y. Du, Z. Peng, Progress and trend of sensor technology for online oil monitoring, Sci. China Technol. Sci. 56 (2013) 2914–2926.
[18] T.H. Wu, J.Q. Wang, Y.P. Peng, Y.L. Zhang, Description of wear debris from on-line ferrograph images by their statistical color, Tribol. Trans. 55 (2012) 606–614.
[19] T.H. Wu, Y.P. Peng, C.X. Sheng, J.Y. Wu, Intelligent identification of wear mechanism via on-line ferrograph images, Chin. J. Mech. Eng. 27 (2014) 411–417.
[20] Spectro Scientific, Lasernet Fines Q200-a Solution to Fluid Analysis Including Particle Count and Particle Shape Classification, Available online: 〈http://www.ship-technology.com/downloads/whitepapers/bunker_fuels/lasernet-oil-analysis-wp/〉. (Accessed 30 July 2017).
[21] D. Filicky, T. Sebok, M. Lukas, D. Anderson, LaserNet Fines-a New Tool For The Fluid Analysis Toolbox, Available online: 〈http://www.machinerylubrication.com/Read/383/lasernet〉. (Accessed 31 July 2017).
[22] Y.P. Peng, T.H. Wu, S. Wang, Y. Du, N.M. Kwok, Z. Peng, A microfluidic device for three-dimensional wear debris imaging, Proc. Inst. Mech. Eng. Part J: J. Eng. Tribol. 231 (2017) 965–974.
[23] S. Raadnui, Wear particle analysisutilization of quantitative computer image analysis: a review, Tribol. Int. 38 (2005) 871–878.
[24] J. Cao, L. Zhang, B.J. Wang, F.Z. Li, J.W. Yang, A fast gene selection method for multi-cancer classification using multiple support vector data description, J. Biomed. Inform. 53 (2015) 381–389.
[25] T.H. Wu, Y.P. Peng, H.K. Wu, X.G. Zhang, J.Q. Wang, Full-life dynamic identification of wear state based on on-line wear debris image features, Mech. Syst. Signal Process. 42 (2014) 404–414.
[26] Y.P. Peng, T.H. Wu, S. Wang, Z. Peng, Oxidation wear monitoring based on the color extraction of on-line wear debris, Wear 332–333 (2015) 1151–1157.
[27] I.O. Pascual, J.S. Almeida, A fast version of the k-means classification algorithm for astronomical applications (research note), Astron. Astrophys. 565 (2014) 1–4.
[28] Y.J. Lei, M. Bennamoun, M. Hayat, Y.L. Guo, An efficient 3D face recognition approach using local geometrical signatures, Pattern Recognit. 47 (2014) 509–524.
[29] C.Q. Yi, R.Y. Zhou, K.N. Hu, Fuzzy support vector machine for breast cancer gene classification, In: Proceedings of the 2017 2nd International Conference on Vision and Computing (ICIVC), Chengdu, China, 2017.
[30] T.T. Chen, S.J. Lee, A weighted LS-SVM based learning system for time series forecasting, Inf. Sci. 299 (2015) 99–116.
[31] G.M. Fung, O.L. Mangasarian, Multicategory proximal support vector machine classifiers, Mach. Learn. 59 (2005) 77–97.
[32] T.H. Wu, Y.P. Peng, S. Wang, F. Chen, N.M. Kwok, Z. Peng, Morphological feature extraction based on multiview images for wear debris analysis in on-line fluid monitoring, Tribol. Trans. 60 (2017) 408–418.