

Knowledge Based Wear Particle Analysis

Mohammad S. Laghari, Qurban A. Memon, and Gulzar A. Khuwaja

Abstract—The paper describes a knowledge based system for analysis of microscopic wear particles. Wear particles contained in lubricating oil carry important information concerning machine condition, in particular the state of wear. Experts (*Tribologists*) in the field extract this information to monitor the operation of the machine and ensure safety, efficiency, quality, productivity, and economy of operation. This procedure is not always objective and it can also be expensive. The aim is to classify these particles according to their morphological attributes of size, shape, edge detail, thickness ratio, color, and texture, and by using this classification thereby predict wear failure modes in engines and other machinery. The attribute knowledge links human expertise to the devised Knowledge Based Wear Particle Analysis System (*KBWPAS*). The system provides an automated and systematic approach to wear particle identification which is linked directly to wear processes and modes that occur in machinery. This brings consistency in wear judgment prediction which leads to standardization and also less dependence on Tribologists.

Keywords— Computer vision, knowledge based systems, morphology, wear particles.

I. INTRODUCTION

ONE of the important areas is in the field of automation of on-line or off-line visual inspection systems of microscopic applications. One such application is the analysis of microscopic wear particles, which are produced in all machines with moving mechanical parts in contact. Any change in the steady state operation of the machine creates a change in the normal wear mechanism. This change in the wear particles or wear debris, transported by a lubricant from wear sites carry with them important information relating to the condition of engines and other machinery. Experts extract this information to diagnose wear producing modes occurring and thus attempt to predict wear failures in machines [1], [2].

The identification and analysis of these particles can be effectively performed by an automated computer system with the ability to make human-like, even better and objective diagnosis. One such computer-based system could release an expert from this task and produce quantitative data not revealed by the human eye. The aim of the overall research is

Manuscript received November 20, 2004.

M. S. Laghari is with the Electrical Engineering Department, United Arab Emirates University, P. O. Box: 17555, Al-Ain, U.A.E. (phone: 97150-662-5492; fax: 9713-762-3156; e-mail: mslaghari@uaeu.ac.ae).

Q. A. Memon, is with the Electrical Engineering Department, United Arab Emirates University, P. O. Box: 17555, Al-Ain, U.A.E. (e-mail: qurban.memon@uaeu.ac.ae).

G. A. Khuwaja is with the Physics Department, Kuwait University, P. O. Box: 5969, Safat 13060, Kuwait (e-mail: khuwaja@kuc01.kuniv.edu.kw).

to develop an image analysis and knowledge based system to classify wear particles in terms of their six morphological attributes of *size, shape, edge detail, thickness ratio, color, and surface texture*. Two types of analysis are carried out to identify particles; one relates to profile attributes – size, outline shape and edge detail, the other covers surface texture classification.

This paper describes the image analysis and knowledge based procedures of *Particle Size Distribution, Particle Shape Determination and Particle Edge Detail Analysis and Particle Texture Classification*. The edge detail analysis procedure is defined in terms of ‘Feret Centric Diameter’ method of boundary recognition. The procedures are integrated into the *KBWPAS* which permits systematic profile and texture analysis of the wear particles.

II. WEAR PARTICLES

The term Wear Particle is associated with the field of “Tribology”. Tribology is the study of wear, friction and lubrication. Particles contained in the lubricating oil can be separated for examination and analysis by using many methods. Different sizes of filters, Ferrography and Magnetic Chip Detectors (*MCD*) are such techniques [3]-[5].

A. Wear Particle Characteristics

The essential requirement in terms of wear is to determine its extent and rate of change in relation to the type of wear and its source. Particles generated by different wear mechanisms have characteristics, which can be identified with the specific wear mechanism. Fig. 1 lists the principal features of wear particle analysis in relation to relevant wear characteristics. Particle features could be divided in terms of their size, quantity, morphology and composition. Particle quantity enables the extent and rate of wear to be monitored quickly and cheaply without stopping machinery until the safe working limits, based on previous experience, is exceeded. Size distribution analysis is quantifiable using automatic particle counting procedures or by devised image analysis. The morphology of particles allied to their composition provides important additional information about the wear condition, specifically the source from where the particle is generated. Wear manifests itself in numerous ways and is likewise categorized according to difference concepts of its mode, underlying mechanisms and its wear severity or rate [6].

B. Wear Particle Classification

Particles are classified in terms of their morphological

attributes. Morphological analysis is an off-line study of wear particles by using a microscope. Experts characterize the particles with particular morphology and relate these to known wear modes. The analysis yields specific information about the condition of the moving surfaces of the machine elements from which they are produced, the mechanism of their formation, and the mode of wear in operation in the system from which they are extracted [7], [8].

III. THE SYSTEM HARDWARE & SOFTWARE

The hardware tool used is the Leica Quantimet Q500MC, an easy-to-use image processing and analysis system. The color image analyzer uses a CCD camera to sample the image.

The image analyzer is controlled by software called *QWIN*. It is an image analysis toolkit running under the industry standard Microsoft Windows environment. The system provides several classes of measurements ranging from semi-manual planimetry to semi-automatic particle sizing [9].

The image analysis system is connected to a Leica M28 zoom stereomicroscope with facility for viewing in transmission and/or incident light. Images of the deposited

The essential measurement procedures are: size distribution, area, positional coordinates, Feret diameter measurements, length, width, perimeter, aspect ratio, roundness-factor, texture image, color, thickness and the count of the particles.

IV. MORPHOLOGICAL DATA PROCEDURES

Procedures are developed to provide a set of data to investigate particle profile and texture analysis, which are based on the four morphological attributes of size, shape, edge detail and texture. Fig. 2 shows few example images of wear particles.

A. Particle Size Distribution

Wear particle size distribution is useful in detecting significant transitions in the wear activity and could provide early indications of impending failure. The ability to identify an increase in particle size can give an indication of caution. In fact, early monitoring was dependent on the parameters of size and quantity only.

The size of the wear particles is computed and classified by the Q500MC by using the particles major dimensions described in terms of six ranges of 0 to 10, 11 to 20, 21 to 50, 51 to 100, 101 to 200, and > 200. These ranges are system dependent and can be modified accordingly.

B. Particle Shape Determination

Shape is an important factor used in the recognition of wear particles after size distribution. Shape features are classified in the form of regular, irregular, elongated and circular. The most subjective way to describe the shape of a wear particle is to compare it to a known object in terms of it being, e.g. *dendritic* or *egg-shaped*, etc. However, such subjective terms can be endless; therefore it is essential to derive some form of standard classification [10].

Dimensionless ratio is one of the techniques to distinguish

and define indices of shape. On this basis, some commonly used dimensionless shape parameters, which are independent of, or in combination with size measurements are: *Aspect Ratio*, *Circularity*, *Rectangularity*, etc. There are many more of these simple form factors. However, the most common features extracted from the image analyzer system to recognize particles according to the above shape factors are: *area*, *length* (length of the longest Feret), *width* (length of the shortest Feret), *perimeter* (boundary of the particle), and *roundness factor* [11], [12].

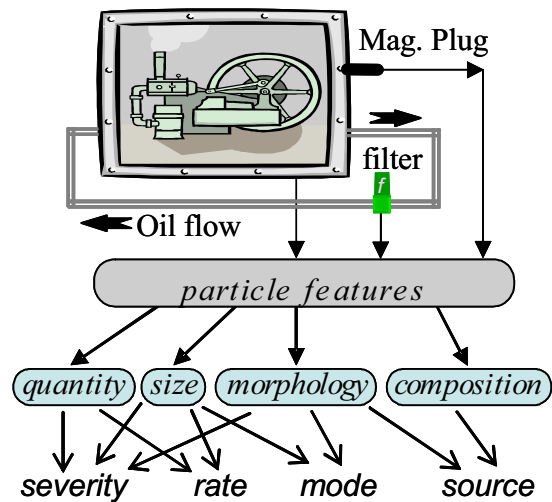


Figure 1: The basic components of wear particle analysis, their characteristics and relationships to wear.

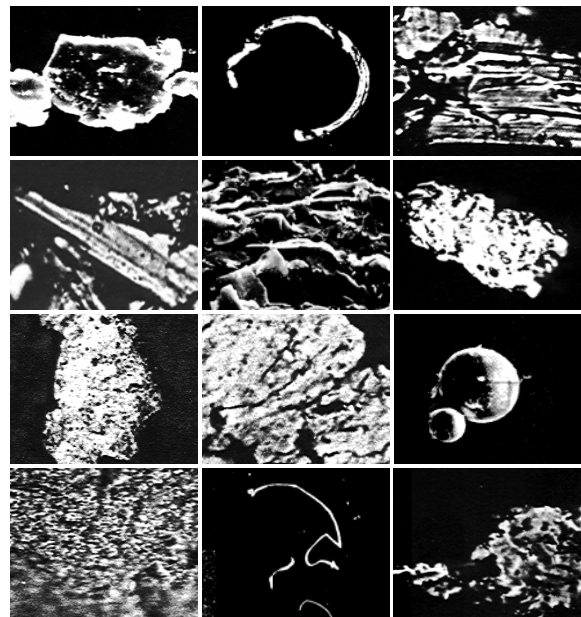


Figure 2: Example images of wear particles.

C. Particle Edge Details

Particle edge detail analysis is based on the perimeter data stored from the Q500MC system procedures and is used to establish particle's edge detail characteristics.

Feret centric diameter method determines the edge detail characteristics of wear particles. It distinguishes between a range of parameters of: smooth, rough, straight, curved smooth, curved rough, and a serrated edge. The method is based on Feret and centric diameter measurements. Feret diameter, sometimes known as *caliper* diameter, is defined as the orthogonal distance between a pair of parallel tangents to the feature, at a specified angle of the scan. In usual terms, Feret 0 corresponds to a feature width while Feret 90 corresponds to height. For a typical particle image, a total of 72 Feret diameter measurements are performed. Each measurement is recorded at an interval of 2.5 degrees ranging from Feret 0 to 180 degrees ($180 / 2.5 = 72$). All measurements are made to pass through the centric of the particle image. The degrees interval depends on the factors of particle size, image magnification, and the specific system from which the particle is produced.

The acquired results are analyzed to distinguish between the ranges of above mentioned attribute features. The absolute difference of the current and previous recorded diameter lengths for each interval of Feret angle performs the analysis. These differential values are then compared with a threshold value. A typical difference greater than the threshold indicates the roughness of the edge, and the total count of differential values greater than threshold specifies the roughness factor [13].

D. Particle Texture Analysis

Texture analysis is carried out on the stored images for seven texture types of *smooth*, *rough*, *striation*, *holes*, *pitted*, *cracked*, and *serrated*. In a texture classification problem, a specific texture sample is assigned to one of a specified number of k possible classes. The decision is taken by a classifier, which is normally fed by data based on measurements made over the entire sample.

A statistical approach is used to describe the texture. It is based on co-occurrence matrices, which describe second-order statistics of the texture, and is usually used for the computation of features, which capture some characteristics of textures such as homogeneity, coarseness and periodicity [14].

The problem associated with the use of co-occurrence matrices is the handling of large amounts of data by the classifier. This is because the number of elements in a matrix is equal to the square of the number of distinct gray levels in the image. Therefore, the original number of gray levels (256) in the image is reduced in order to make the co-occurrence matrix smaller and hence reduces the amount of mathematical calculations involved. Dividing the gray levels into a small number of bands having equal widths performs this. Three different band numbers of 4, 5, and 6 have been used [15].

Since the number of elements in a matrix is equal to the square of the number of gray levels in the image, therefore the

resulting matrices associated with these bands are '4 x 4', '5 x 5', and '6 x 6', respectively. The number of the bands used for current work is 6, which results in an image having new gray levels ranging from 0 to 5 and hence a matrix of '6 x 6' is computed. Therefore, a total of from 0 to 255 gray levels are reduced to from 0 to 5 by a method called *gray scale reduction*.

The co-occurrence matrix is related to the estimation of the second-order probability density function $f(i, j, dist, ang)$. It is defined as the probability of joint occurrence of two gray levels, 'i' and 'j' in a digital image, such that the distance between the two corresponding pixels is 'dist' and at a direction defined by the angle 'ang'. Therefore, a matrix can be computed by counting the number of times a pair of gray levels occurring at a separation of *dist* pixels and in a direction specified by *ang* degrees [16].

For each image sample, four co-occurrence matrices are computed with each matrix corresponding to one of the four directions, i.e., $ang = 0^\circ, 45^\circ, 90^\circ, \text{ and } 135^\circ$, between a pair of adjacent pixels. The respective elements in the four matrices are averaged in order to produce a rotation invariant matrix.

Feed-forward neural structures using a single hidden layer are used as classifier for texture. A supervised learning scheme using the back propagation algorithm is implemented. The input database consists of a set of input vectors together with the corresponding classifications. Each input vector consists of a number of components which are equal to the number of elements in the co-occurrence matrix. Several iterations are required to train the network so that it can in the future classify new unseen vectors and assign each one to a specific texture class.

V. KNOWLEDGE BASED SYSTEM

A. Wear Particle knowledge modeling

The approach to modeling wear particle knowledge can be listed under four items; particle types, morphological attributes, priorities, and rules. The relationship between the wear particle properties and the condition under which they are formed enables particles to be classified in terms of a number of types. Each particle type gives a different clue about the machine condition and performance. *Rubbing*, *cutting*, and *severe sliding wear* are the few examples of wear particles. Current research in the field has suggested 29 different types of wear particles [11].

The described six morphological attributes are classified by their options or features. For example, edges of a wear particle can be smooth, rough, straight, serrated, or curved. Particle attribute priority gives each particle type a level of priority. This is essential for identification where in some situations the individual features of the six attributes alone are not sufficient to distinguish between some particle types, since many particle types have some attribute features in common.

The process purpose of identifying particle types consists of matching features extracted from a given input particle with those of the wear particle type models. After extracting wear

particle knowledge one has to ensure that an appropriate system environment is made available to represent and manipulate the wear particle knowledge. *KBWPAS* is developed for this purpose. The system consists of knowledge representation phase connected with an inference engine integrated into a user interface.

B. Knowledge Engineering and Representation

Knowledge representation and data base creation is one of the important aspects of knowledge based systems because it determines the necessary acquisition and reasoning procedures. It has been described that a typical particle can be identified with the help of six attributes; therefore the wear knowledge needs to be highly structured in order to define the relationship between the particle types and their attributes.

The process of the creation of wear particles is system and environment dependent. The *KBWPAS* is not devised as a universal particle identification system but more suitably as an adaptable system. Therefore, it is important to separate particle knowledge from knowledge manipulation and processing. As a consequence, the rule based used for the diagnosis of particle type is read in from a text file and is thus independent of program code. Moreover, the attribute list of options is also read in from another text file. For example, one rule base can be developed for Rolls-Royce engines, whereas another for Tornado jet engines.

C. System Development

The basic approach used in developing *KBWPAS* involves direct interaction between the particle analyst and the AI Expert. Through systematic interrogation the latter extracts from the former his knowledge and experience and decides how it should be represented in the system and then devises a set of rules to control its functions. Fig. 3 illustrates the strategy of the knowledge based system.

The achieved information is represented in two ways. First, in the form of a *controller* this stores the information such as total number of particles, number of attributes, and number of options for each attribute. The second is wear particle details from a library of 29 particle type files. The information read is according to the *controller* specifications.

From the different types of knowledge representation techniques, *frame* is the technique used to provide the structured knowledge of representing an object or class of objects for the system. A frame is a method of organizing and representing knowledge which can be in the form of a mini-database consisting of slots containing data. Frame knowledge representation's main advantage is that it facilitates the inheritance of properties and values for an entity and it also participates in the reasoning process.

Wear particle knowledge is described as a class which is used to define particle types, their attributes, and their relationships. These class members are represented using three frames as shown in the following:

- The six wear particle morphological attributes as

deduced from earlier mentioned procedures.

- Priorities related to each attribute for the 29 wear particle types.
- The percentage weighting factor associated with each priority.

The percentage weighting factor is important for overall wear judgment. A typical particle slide contains 100's of particles. If for example, 70% of the particles are identified as the benign rubbing wear, then the resulting wear judgment will be of a *normal* nature.

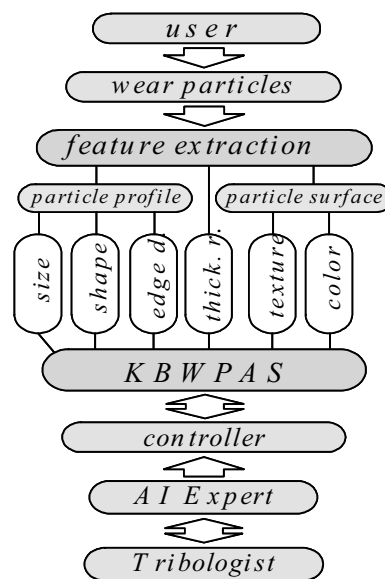


Figure 3: Strategy of knowledge based system.

D. Inference Engine

The logic operation of the inference engine is the process of matching. This is the particle recognition of the system. It is divided into rule sets, each dealing with a specific attribute. The inference engine method of forward chaining is used as the matching process. According to the quantification rules to reason with class members, the decision as to which particle type the input particle belongs to, is determined by the particle information and searching through all the class members to find an acceptable match. Three different resulting situations can occur after the search process:

- The particle is identified.
- The particle does not have sufficient information to be identified.
- There is more than one type identified for a single entry.

The first conclusion is what the system is supposed to do. This situation provides the necessary wear judgment and needed recommended action. The second can occur where the

input particle is not properly defined by the system attributes. The third reveals that two or more particle types have the same options for their attributes. This is due to the fact that some particle types are closely related and therefore the attributes alone cannot identify each individual particle type. The remedy is to prioritized attributes for specific particle types. For example, shape and texture attributes are important for ferrous particle types. However, for other types such as oxide and non-metallic, color is an important attribute.

Attribute priority is also important for the reason that some particle types have more than one option to describe the attribute. For example, a particle *ferrous laminar rolling fatigue* is more positively identified with holes and cracks on the particle surface. Hence, this particle has the highest priority in the texture attribute priorities.

REFERENCES

- [1] H. P. Jost, "Tribology - Origin and Future," in *Wear*, vol. 139, 1990, pp. 1-17.
- [2] B. J. Roylance and T. M. Hunt, *Wear Debris Analysis*, Coxmoor Publishing, Oxford, 1999.
- [3] W. W. Seifert and V. C. Westcott, "A method for the study of wear particles in lubricated oil," in *Wear*, vol. 21, 1972, pp. 27-42.
- [4] T. M. Hunt, *Handbook of Wear Debris Analysis and Particle Detection in Fluids*, Elsevier Science, London, New York, 1993.
- [5] A. C. Cumming, "Condition monitoring today and tomorrow - an airline perspective," presented at the 1989 Int. Conf. *COMADEN 89*, Birmingham, U.K.
- [6] T. P. Sperring and B. J. Roylance, "Some recent development in the use of quantitative procedures for performing wear debris analysis," *JOAP International Condition Monitoring Conference*, Mobile, AL, 2000, pp. 205-210.
- [7] G. A. Khuwaja and M. S. Laghari, "Computer vision techniques for wear debris analysis," in *Int. J. Computer Applications in Technology*, vol. 15, no. 1/2/3, 2002, pp. 70-78.
- [8] M. S. Laghari and A. Boujarwah, "Wear particle identification using image processing techniques," in *ISCA 5th Int. Conf. on Intelligent Systems*, Reno, Nevada, 1996, pp. 26-30.
- [9] Leica Cambridge Ltd., *Leica Q500MC Qwin User Manual*, Leica Cambridge Ltd., U.K., 1994.
- [10] H. Xu, A. R. Luxmoore and F. Deravi, "Comparison of shape features for the classification of wear particles," in *Engineering Applications of Artificial Intelligence*, vol. 10, no. 5, 1997, pp. 485-493.
- [11] S. Raadnu, *Wear Particle Characterisation Utilising Computer Image Analysis*, Ph.D. Thesis, Dept. Mech. Eng., University of Wales, Swansea, 1996.
- [12] B. J. Roylance, "Wear debris analysis for condition monitoring," in *INSIGHT* 36, vol. 8, 1994, pp. 606-610.
- [13] M. S. Laghari, "Shape and edge detail analysis for wear debris identification," in *Int. J. of Computers and their Applications*, vol. 10, no. 4, 2003, pp. 271-279.
- [14] A. K. Muhamad and F. Deravi, "Neural networks for texture classification," in *IEE 4th Int. Conf. on Image Processing and its Applications - IPA'92*, Maastricht, The Netherlands, 1992, pp. 201-204.
- [15] J. Garcia-Consuegra and G. Cisneros, "Integration of gabor functions with cooccurrence matrices: Application to woody crop location in remote sensing," in *IEEE Int. Conf. on Image Processing*, vol. II, Kobe, 1999, pp. 330-333.
- [16] M. S. Laghari, "Recognition of texture types of wear particles," in *Int. J. of Neural Comp. & Applications*, vol. 12, 2003, pp. 18-25.