Wear Particles Surface Identification Using Neural Network

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Summary
This paper investigates the analysis of microscopic particles generated by wear mechanisms using image processing techniques. Particles are classified using their visual and morphological attributes to predict wear failure in engines and other machinery. The paper describes the stages of identification processing involved including a neural network system to classify wear articles in terms of their surface texture.

Key words:
Wear Particles, Tribology, Texture Attributes, Texture Description, Neural Network.

1. Introduction

The term wear particle comes from the field "Tribology". The concept of tribology was first enunciated in the year 1966 by the British Department of Education and Science. It was defined as "The Science and Technology of interaction surfaces in relative motion and of associated subjects and practices" [1]. Microscopic wear particles in oil carry important in formation concerning the condition of engines and other machinery. Specialists can extract this information to monitor the operation of the machine and ensure safety, efficiency, and economy of operation.
Machine wears have been monitored by using techniques such as X-rays and ultrasound. A new method was developed in which lubricating oil samples were prepared in the form of slides of the microscopic wear particles. When studied by the experts of the field, the samples provide a wealth of information on the wear process involved and on the state of the machinery.
In this paper a system is presented to monitor the wear process using computer vision and image processing techniques applied to wear particle analysis. The aim is to classify these particles and using the information obtained to predict wear failure modes in engines and the machinery. This obviates the need for specialists and the reliance on human visual inspection techniques. Using the proposed techniques for monitoring at an early stage can avoid expensive equipment failure and the loss of valuable production time.

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2. Wear Patiles Classification

Particles generated by different wear mechanisms have characteristics which can be identified with the specific wear mechanism. Rubbing wear or normal wear particles are generated as the result of normal sliding wear in a machine. These are found in the lubricant of most machines in the form of platelets. Magnetic Chip Detector (MCD) is a method used for extracting particles. Magnetic plugs are small removable units fitted with a powerful permanent magnet and situated in convenient positions in the machine. Due to magnetism, particles stick to the plug and later the plug is wiped on a slide. The particle size is typically greater than 100/m.
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. Particles can be classified in terms of their compositional and morphological attributes. The work described in this paper mostly relates to texture attribute which is one of the morphological attributes of wear particle.
Grey scale image of the particles is transmitted from the field of view in the microscope via the camera and is stored in the video R.A.M of the frame grabber. In this procedure the system automatically selects all the wear particles in the image. This process is suitable for the wear particle slides where the particles are evenly scattered in such a way that they are not touching each other or are overlapping The grey scale image of the wear particles is stored for processing.

3. Analysis

Procedures are developed to provide a set of data to represent the morphological attributes of shape, edge, size, texture, color, and thickness ratio. In this paper, the texture attribute is used to investigate the identification of wear particles in terms of their surface texture. Wear particles have been classified in seven texture classes as shown in Figure 1. In texture classification problems, an observed texture sample is assigned to one of K possible texture classes on the basis of measurements made over the entire sample.

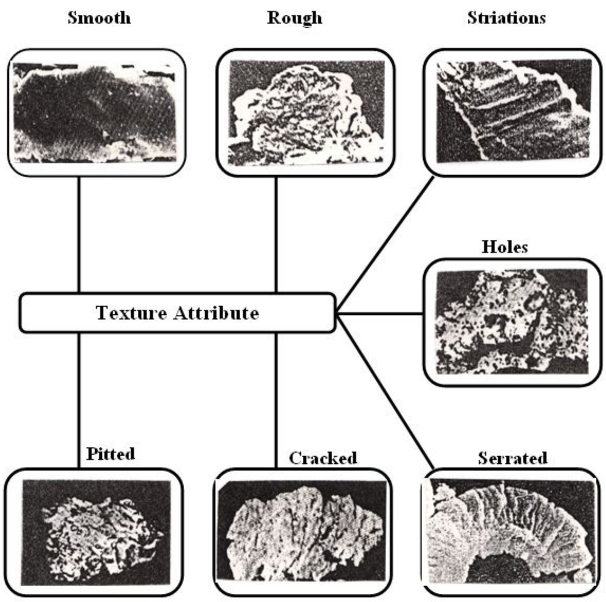

Figure 1. Neural classifier with a single hidden layer

Texture analysis plays an important role in pattern recognition and there are two conventional approaches which are usually associated with texture description. These are statistical and structural approaches. The statistical analysis approach is very frequently based on co-occurrence matrices which describe second-order statistics of the texture. The co-occurrence matrices are usually used for the computation of some features which capture some characteristic of textures such as homogeneity, coarseness and periodicity.

The individual classification capability of such features has recently been examined. The relative merits of different combinations of these features are evaluated. A best combination for maximum classification is hence established. The co-occurrence matrices have also been utilized directly for classification. The original number of gray levels in the images (256) is reduced in order to make the co-occurrence matrix smaller and hence reduce the number of mathematical computations. It is suggested that the amount of information lost that way is less than that associated with the extraction of features and hence better performance can be achieved. In all cases, a feed-forward neural network is used for classification. The classifier is required to distinguish among seven different texture classes of wear particles as shown in Figure 1. High recognition rates are obtained when tests are made on new unseen data.

Here, the wear particle images are classified based on data extracted directly from the co-occurrence matrices. The gray levels in the original image are divided into a small number of bands having equal width. Three different band numbers, namely 4 , 5 and 6 are used. Since the number of elements in the co-occurrence matrix is equal to the square of the number of distinct gray levels in the image, matrices of 4×4, 5×5 and 6×6 are consequently computed.

The co-occurrence matrix (or the spatial gray level dependence matrix) is related to the estimation of the second-order probability density function, f(i, j, d, a). For a digital texture image, the function, defines the probability of joint occurrence of two gray levels, i, nad j, given that the distance between the two levels is d at a direction defined by the angle a. Therefore, each matrix can be computed by counting the number of times the pair of gray levels accounts at separation d pixels and in the direction specified by a degrees.

The following example shows a small digital image (on the left) and its corresponding matrix (on the right). The matrix is computed for horizontally adjacent gray level pairs (d = 1 and a = 00). Note that the size of the matrix does not depend on the size of the image but rather on the maximum gray level value in the image.

0	0	1	1
0	0	1	1
1	0	2	2
2	1	1	0

4	4	1
4	6	1
1	1	2

For each image sample, 4 co-occurrence matrices are computed with each matrix corresponding to one of the four main directions, a=00, 450, 900 and 1350 between a pair of adjacent pixels. The respective elements in theses 4 matrices are averaged in order to produce a rotation invariant matrix. Only rotation invariant matrices are considered for this work. Each image sample being used here is obtained from a different slide. This poses a new challenge to the algorithm. Not only it has to cope with orientation, but it has also to deal with samples captured at different resolutions.

4. Neural Network Classifiers

Feed-forward neural network structures using a single hidden layer are used as classifiers 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 is equal to the number of elements in the co-occurrence matix. Several iterations are required to train the network but once it is trained, it is supposed to classify new unseen vectors and assign each one to a specific texture class.

Figure 2 shows a layout of the structure of the neural classifier used for the texture. It consists of three layers, the input, the hidden and the out put layer. The input layer consists of a number of nodes which is equal to the number of elements in the co-occurrence matrix; 16, 25 or 36 (11, in the figure, is the first element in the matrix, 12 is the second element, … etc). The hidden layer consists of a variable number of node in the input layer is connected to each single node in the hidden layer. Similarly, each node in the hidden layer is connected to each single node in the output layer. All connections between pairs of nodes in adjacent layers carry a weight which keeps changing until the training phase has been completed.

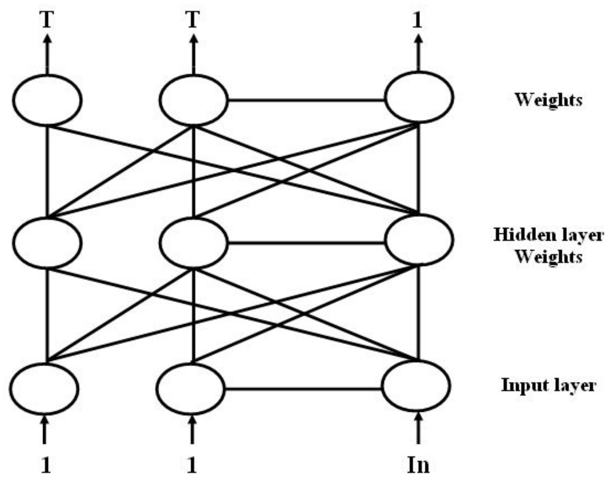

Figure 2. Neural classifier with a single hidden layer

5. Conclusion

Manual and automatic systems are described which will replace experts in the field of wear particle monitoring. Though preparation of the particle slides needs to be improved, the system is capable of extracting quantitative information from low quality slides. Texture analysis was used to extract features of wear particles. Neural Networks was used to classify the wear particle attributes to classify particles in relation to the wear process and permits a judgment to be made about the wear state. More work needed to be done on the other attribute color and thickness ratio of the wear particles.

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