A TEXTURE CLASSIFICATION SYSTEM USING COOCCURRENCE MATRICES

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ABSTRACT
Microscopic wear debris is produced in all machines containing moving parts in contact. The debris (particles), transported by a lubricant from wear sites; carry important information relating to the condition of the machinery. This information is classified by six morphological attributes of particle size, shape, edge details, color, thickness ratio, and surface texture. The paper describes an automated system for surface features recognition of wear particles by using artificial neural networks. The aim is to classify these particles according to their morphological attributes and by using the information obtained, to predict wear failure modes in engines and other machinery. This approach will enable the manufacturing industry to improve quality, productivity and economy. The procedure reported in this paper is based on gray level cooccurrence matrices that are used to train a feed-forward neural network classifier in order to distinguish among six different patterns of wear particles. The patterns are: *smooth, rough, striations, pitted, cracked,* and *serrated.* An accuracy classification rate of approximately 95% has been achieved and is shown by a confusion matrix.

KEYWORDS
Wear Particles, Cooccurrence Matrices, Texture Analysis, Neural Networks, Artificial Intelligence.

INTRODUCTION
Computer vision is a process to locate and recognize objects in digital images. It is a relatively new and fast growing field and involves techniques from image processing, pattern recognition and artificial intelligence. Image segmentation is concerned with splitting an image up into segments or regions such that each holds some property distinct from its neighbors. It is a basic requirement for the identification and classification of objects in a scene. Segmentation can be approached from two points of view; by identifying edges and shapes that run through an image, or by identifying regions such as texture [1], [2].

Computer vision has been used in the field of automation of inspection systems. These inspection systems include applications where information is retrieved by using microscopes. One such application is the analysis of microscopic wear particles that are produced in all machines with moving mechanical parts. During the initial run period of a machine, large amount earlier and a steady state later of wear debris is produced due to the contact between new mechanical parts. Any change in the steady state operation of the machine, creates a change in the normal wear mechanism. The associated changes in the microscopic wear particles, transported by a lubricant from wear sites, carry important information relating to the condition of engines and other machinery. Experts in the field extract this information to diagnose occurring wear modes and thus attempt to predict wear failures in machines.

The aim of the current work is to identify particles according to their surface textural features by using artificial neural networks. A comparison between cooccurrence matrices representing six different texture classes is described. Based on these comparisons, matrices of reduced sizes are utilized to train a feed-forward neural network classifier with a single hidden layer in order to distinguish between the various texture classes. Experiments are performed by varying the number of nodes in the hidden layer. A classification accuracy of approximately 95% is achieved and is shown by a confusion matrix.

WEAR PARTICLE DEFINITION
The term *Wear Particle* is associated with the field of "Tribology" which is the study of wear, friction and lubrication [3].

An image-processing computer may effectively perform the identification and analysis of these particles with the ability to make 'human-like' diagnosis. One such computer based automated system could release an expert from this task and produce quantitative data not revealed by the human eye. Using the proposed techniques for monitoring at an early stage, expensive equipment failure and the loss of valuable production time can be avoided.

Particle Viewing and Separation
Using techniques such as X-rays and Ultrasound monitors machine wear. Particles contained in the lubricating oil can be separated for examination and analysis using several methods. An analytical method, developed in 1971, permits particles to be deposited on a glass slide, and identified by using a microscope.

Different size filters are used in machines to separate particles from the lubricant [4].

Ferrography is another technique in which wear particles are separated from the lubricant and arranged according to size on a transparent substrate for analysis, thereby allowing further observation of the particles. The particle size range is typically between 1 to 100 μm [5].

The MCD *(Magnetic Chip Detectors)* or *Magnetic Plugs*, is yet another 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 substrate or slide. The particle size in this case is typically greater than 100 μm [6].

Examples of Wear Particle

Particles generated by different wear mechanisms have characteristics, which can be identified with the specific wear mechanism. The following are a few examples of wear particles [4].

Rubbing wear or normal wear particles are generated as the result of normal sliding wear in a machine. The wear producing this particle is of benign nature and has a characteristic of normal rubbing wear. These are found in the lubricant of most machines in the form of platelets, typically ranging in size from 0.5 to 15 μm. Rubbing wear particles usually have a smooth surface texture.

Cutting wear or abrasive wear particles are generated as result of one surface penetrating another. It takes the form of spirals, loops, and long bent wires similar to the lathe-machining swath. The typical sizes of a cutting wear particle ranges from 2-5 μm wide to 25-100 μm long. Concentrations in such particles indicate severe wear mode and imminent machine failure. These particles do not have a particular surface texture, except that the spirals are very smooth and glossy.

Severe sliding wear particles are generated when the wear surface stresses become excessive due to poor lubrication, load and/or speed. These wear particles range in size from 15 μm up. Particles generated from severe sliding have very distinct surface features of striation marks. Again, concentration of such particles, and also with more prominent striation marks, indicate severe wear mode.

Rolling Fatigue particles are generated as a result of rolling bearing fatigue. There are three types of rolling fatigue particles. The first is Fatigue Spall particles which constitute the actual material removed as a spall opens up. The second is the spherical particles which are generated in the bearing fatigue cracks. The third type is the Laminar particles.

Laminar particles are associated with rolling bearing fatigue. These are very thin free metal particles between 20 and 50 μm, and are generated by the passage of wear particles through a rolling contact, possibly after adhering to a rolling element. Its surface features are recognized by frequent occurrence of holes in the particle. Research in the field has suggested 29 different types of wear Particles [7].

Wear Particle Characteristics

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.

Particle features could be divided in terms of their *size, quantity, morphology* and *composition.* From these four features, tribologists know that quantity of the particles give the severity and rate at which they are generated, composition indicates the source of the generated particles, morphology indicates the source, type and rate of generation, and likewise particle size gives the rate, type and severity [8].

Wear Particles Classification

Particles can be classified in terms of their *compositional* and *morphological* attributes. The compositional attributes represent whether the particles obtained are metallic or non-metallic, if metallic, then ferrous (magnetic) or non-ferrous metals, etc.

Morphological analysis is an off-line procedure carried out by using a microscope. Experts in the field characterize the particles in terms of their morphological attributes and relate them to known wear modes. The analysis yields specific information about the condition of the moving surfaces of the machine elements from which they were produced, the mechanism of their formation, and the mode of wear [9].

A typical particle is viewed for its shape; such as regular, irregular, elongated, etc, its edge details; such as curved, straight, rough, etc, its size; usually increase in benign size is an indication of abnormal wears, its color; gives an indication of the source of particle generation, its thickness ratio; indication of some abnormalities in relation to size. Particle is carefully examined for its textural attribute. Specific texture patterns are clues for known wear modes. As mentioned earlier that the particle types such as laminar and severe sliding have holes and striation marks, respectively. Particles generated due to general fatigue typically results in a surface texture of pitting marks, which is another example of the importance of the texture attribute.

SYSTEM HARDWARE & SOFTWARE

The system hardware consists of an optical microscope with facility for viewing in transmission and/or incident light. . Images of the deposited particles are transmitted from the field of view in the microscope via a CCD color camera to an IBM compatible computer. The computer contains a Transtech motherboard with space to plug in up to 10 transputer modules (TRAM's). The motherboard is equipped with a fully programmable frame-grabber with one Mbyte of frame-store and four Mbytes of program memory. A graphics processor TRAM displays the image captured by the frame-grabber. The system is capable of processing 25 frames of 512 by 512 pixels (picture elements) per second [10].

The language used for programming the transputer system is `Parallel C' from the Company 3L. 3L's Parallel C can be used to write conventional sequential programs or use the full support for concurrency offered by transputers. The treatment of parallel processing in transputer systems is based on the idea of communicating sequential processes. In this model, a computing system is a collection of concurrently active sequential processes, which can only communicate with each other by channels. Although, use of parallel processing does not bare much significance for texture recognition only, but will be quiet essential when particles are recognized by using all the six morphological attributes.

ANALYSIS

Procedures are developed to provide a set of data to represent the morphological attributes of shape, edge detail, size and texture. Two types of analysis are carried out; one deals with the classification of particle profile attributes of size, shape and edge detail. The other is *Texture Analysis*, which is to classify the particles in terms of their surface texture.

Profile Analysis

The profile analysis is carried out on the perimeter or profile data and produces data in the form of particle size, major and minor dimensions, size averages, aspect ratio, roundness factor, and edge details analysis [11], [12], [13].

Texture Analysis

Texture analysis procedure is designed to execute within a devised "Wear Particle Texture Analysis" *(WPTA)* package. It is a multiple window, hierarchical interactive graphics interface that controls the software environment.

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 cooccurrence 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], [15], [16].

The problem associated with the use of cooccurrence 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 cooccurrence 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.

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 '4×4', '5×5', and '6×6', 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 6×6 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* [17].

Cooccurrence Matrix: The cooccurrence 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.

Fig. 1 shows an example of a digital image and its corresponding cooccurrence matrix for 6 bands. The matrix has been computed for horizontal adjacent gray level pairs, where the distance between pairs is *dist* = 1(adjacent) and at an angle of *ang* = 0 (horizontal in both directions). The Figure also shows how the cooccurrence matrix coordinates of (3, 2) computes the value of 4 from the digital image. The generated matrix is symmetric about the main diagonal. The data extracted from the matrix is used directly to feed the neural network classifier [18].

0	1	4	3	1	2 ←	3
1	5	2	2	1	3	0
4	3	1	2	0	0	5
1	2	2	1	1	4	3
3	3	3 →	2	1	5	5
1	1	4	4	5	3 →	2
3 →	2	4	5	3	1	2

digital image

2	1	1	1	0	1
1	4	7	4	3	2
1	7	4	4	1	1
1	4	4	4	3	2
0	3	1	3	2	2
1	2	1	2	2	2

cooccurrence matrix

Fig. 1. Digital image gray level values and its corresponding six-band cooccurrence matrix

The Neural Network Classifier: A feed-forward neural network with a single hidden layer is used as the classifier in which a supervised scheme using the backpropagation algorithm is implemented. The algorithm requires several iterations in order to train the network. The input database consists of a set of input vectors included with the corresponding classifications. Each input training vector consists of a number of components, which is equal to the number of utilized features, plus the number of target texture classes. A trained network is designed to classify new unseen vectors and assign each one to a specific texture class [19].

The classifier consists of three layers: input, hidden, and an output layer. The input layer consists of a number of nodes, which is equal to the number of elements in the input vector. The hidden layer consists of a chosen variable number of nodes. The output layer consists of six nodes, which represent the proposed wear particle texture classes. All connections between pairs of nodes in adjacent layers carry a weight, which keeps changing until the training phase is completed. Once this is achieved, the network is ready for use as a classifier.

EXPERIMENTS

Texture analysis is carried out on the stored images for six texture types of smooth, rough, striation, pitted, cracked, and serrated.

Gray scale images of size 512×512 are captured from wear particle slides and displayed on the screen. The cursor is used in a *manual selection* procedure to select a sub-image of size 64×64 pixels on the particle image. Therefore, each particle image gives a choice of 64 $(512 \times 512 \div 64 \times 64)$ sub-images. For the texture analysis experiment, a total of 48 sub-images per texture class are extracted from a reasonable number of particle images, which are in relation to the size of the particle and the region of interest in that particle. The extracted sub-images for each texture class are then distributed equally (at random) for training and testing purposes in such a way that each of the training and test file consisted of 144 vectors (24×6).

For each texture sample, not one but four cooccurrence matrices are computed. Each matrix corresponds to one of the four main directions $(ang = 0^\circ,\ 45^\circ,\ 90^\circ,\ 135^\circ)$ between a pair of adjacent pixels. The respective elements in these four matrices are averaged in order to produce a rotation invariant matrix. The input to the classifier is based directly on this rotation invariant matrix.

As the matrix is symmetric along the main diagonal, this further reduces the input vectors of the classifier such that only 21 values of one end of the diagonal are fed instead of all 36 values. A texture classification system using cooccurrence matrices is shown in Fig. 2.

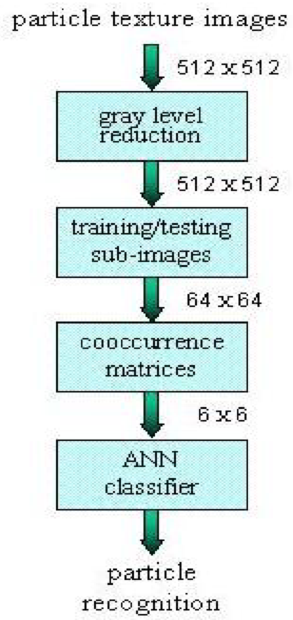

Fig. 2. The structure of WPTA system using cooccurrence matrices

For the experiment, the classifier uses small to medium size of node numbers for the hidden layer. This is due to the limited number of input and output (6) vectors. Consequently, experiments are performed with the hidden layers of 4, 8, 12, 16 and 20 nodes. Fig. 3 shows a typical output generated by the WPTA classification package. The package identifies the particle texture as well as displays the particle sub-image. The shown example is classified as pitted with some concentration of roughness & serration.

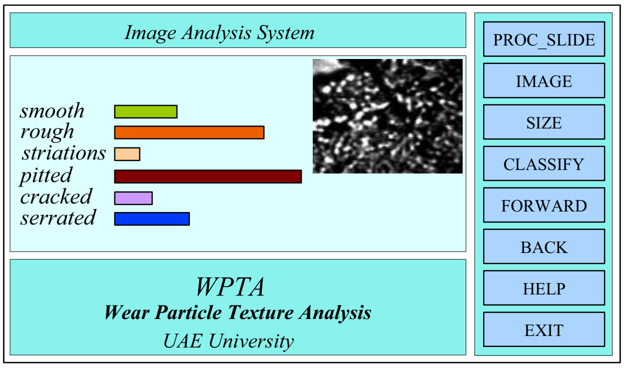

Fig. 3. A typical output screen of WPTA package with a particle sub-image

In the testing phase, the network with four hidden nodes achieved a maximum classification rate of 93%. All the other four networks achieved a maximum rate of 95%. This rate corresponds to a correct classification of 137 out of a total of 144 unseen test samples.

It is evident from the above Figure that because of similarity of many textural features, the specific particle can be classified as rough as well as pitted. It is suggested that the reason for this could be the slight variation in the surface texture between different particles, or even different areas in the same particle.

As indicated, texture is an important attribute for the recognition of wear particles. The particle with striation marks as an example is produced due to *severe sliding* under pressure. These particles are generated when the wear surface stresses become excessive due to poor lubrication, load and/or speed. A concentration of such particles indicates a severe wear mode and hence needs immediate attention.

CONCLUSION

Computer vision and image processing techniques are used to collect important quantitative and other information from wear particle images. The paper describes an important attribute of texture identification system for the analysis of microscopic wear particles. A cooccurrence matrices approach is used to prepare data from an 64×64 image to a matrix of size 6×6. This reduced image is fed to a classifier based on an artificial neural network with a single hidden layer. Experiments performed indicated that by varying the number of nodes in the hidden layer, a high classification rate of approximately 95% is achieved.

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