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AN EXPERT SYSTEM TO IDENTIFY WEAR PARTICLES

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Abstract

The paper investigates the identification of microscopic particles generated by wear mechanisms using computer vision and image processing techniques. Particles are classified by using their visual and morphological attributes to predict wear failure modes in engines and other machinery. The stages of processing are described in the paper, including an adept system to classify wear particles in terms of their six morphological attributes.
Index Terms— Tribology, Wear Particles, Expert System, Morphological Analysis.

I. INTRODUCTION

The location and recognition of objects in digital images are important aspects of Computer Vision. These tasks require the use of techniques from image processing, pattern recognition and artificial intelligence, which have been used in diverse areas of applications. An important aspect of their applications is in the automation of visual inspection systems.

One such application is the analysis of microscopic wear particles, which are produced in all machines where moving mechanical parts come 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 carries important information relating to the condition of engines and other machinery. Experts extract this information to diagnose wear-producing modes occurring thus attempting to predict wear failures in machines to ensure safety as well as achieve increased efficiency and economy of operation [1]-[5].

The term *Wear Particle* comes from the field of "Tribology". The concept of Tribology was first enunciated in the year 1966 by the British Department of Education and Science and this concept was characterized as *"The Science and Technology of interacting surfaces in relative motion - and of associated subjects and practices"* [6].

An automated computer system with the ability to make human-like or even better objective diagnosis can effectively recognize and analyse these particles. One such computer-based system could be effectively used as an alternate to a *'Tribologist'* that can produce computable data not visible to the human eye. Conversely, the objective of this investigation is to cultivate an expert system to identify wear particles in terms of their six defined morphological attributes of *shape, edge details*, *size*, *surface texture*, *color, and thickness ratio* [7].

Wear particles are produced in all machines containing moving parts in contact. Ideally, during the initial period of machine operation, a relatively large amount of wear debris is produced due to many contacts occurring between new parts. Later, the wear reaches a lower, steady state, which results in the generation of smaller quantities of wear debris. Any ensuing change in the steady state condition of the machine will have the tendency to cause an alteration in the benign wear mechanism. Thus, the microscopic wear particles, transported by a lubricant from wear sites, carry important information relating to the condition of machinery. Tribologists extract this information, which can be utilized into a knowledge-based system commonly called as an "Expert System" [8].

Wear can be monitored by using techniques such as X-rays and ultrasound. Another method utilises lubricating oil samples taken from the machine such that the wear debris contained within the oil is separated using magnetic force and deposited on a clean (glass) substrate. When studied under an optical or scanning electron microscope, a wealth of information about the wear process involved is available which indicates the wear state of the machine. Studying the particles morphology, for instance, reveals information about the type of wear and this aspect is exploited particularly to detect abnormal wear modes [9].

The aim of conducting wear particle analysis is thus to identify particles and use the information obtained to predict wear failure modes. By utilizing these techniques, expensive equipment failure and the loss of valuable production time can be avoided [10]-[12].

II. BACKGROUND INFORMATION

The following are few of the investigated works on expert systems and knowledge based wear particles identification systems.

The authors in this paper have proposed to employ Extreme Learning Machine (ELM) for ferrography wear particles image recognition. They extracted the shape features, color features, and texture features of five typical kinds of wear particles as the input of the ELM classifier and set five types of wear particles as the output of the ELM classifier. Therefore, the novel ferrography wear particle classifier is founded based on ELM [13].

The authors of this reference paper have described a process to classify wear debris by identifying their morphological attributes. The classification allows automated particle identification without any help from human experts of the field. Multi-Layer Perceptron (MLP) is used to analyse precise types of wear particles. Size and aspect ratio were the main morphological attributes used among others to classify wear debris [14].

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The authors have developed a Knowledge Based Wear Particle Analysis System (KBWPAS) in this reference paper. The knowledge of the human experts of the field is associated with the six morphological attributes of wear particles. An automated system to identify wear particles is the result of this investigation and this identification is directly linked to wear processes and modes occurring in machinery [15].

This paper introduces a wear particles analysis system that is based on machine learning to classify wear debris. The investigated method depends on wear particles classification resulting into several classes dependent on the origin of such particles [16].

The authors of this paper describe a Particle Expert System (PES), to improve particle classification in the automotive production process in terms of casts, burrs, and chips. The PES assists the user to trace the origin of wear particles with high reliability and a stable success rate [17].

The authors have described an earlier version of expert system, which permits systematic morphological analysis of wear debris [18].

The authors of this paper have purposed a two-level belief rule bases (BBRB) system where the 2-D and 3-D features of wear particles are used as ancestor attributes on each level. The investigated BBRB system can concurrently process uncertainties of quantitative and qualitative wear information [19].

III. WEAR PARTICLE TYPES

Wear Particles have characteristics that associate with the conditions under which they are formed and typically give specific details about the condition of the surfaces from which they originate. This is important in determining whether the component or machine is in a danger of failure. Particle shape and size are important, including the color and surface textures, which are also useful in ascertaining the type of materials in terms of ferrous or non-ferrous including the silica particle.

Particle types can be divided into six main groups of:

Rubbing or Pitting Wear: generated because of normal sliding of metal against metal in machine parts such as gears. The particles are identified by their smooth flat shape and relatively high length to thickness ratio. The particle size is generally small. The wear producing this particle type is of a benign nature and is commonly referred to as acceptable normal rubbing wear. However, there will be an increase in particles produced if lubrication system changes from normal to contaminate. The concentration of particles typically increases with the rate of particle generation. Consequently, particle size also increases. This high wear rate will cause a rapid wear-out of the machinery.

Severe Sliding Wear: when rubbing wear particles pass through small and tight clearances, such as those typically found in bearings, which may result in severe sliding wear particles being formed. These are also often referred to as high stress, sliding particles. The high stress sliding of this wear mode causes the shape and surface of the particle to change compared to normal rubbing wear. The shape becomes more elongated and some edges of the particle are no longer smooth. The surface typical has deep parallel striation marks due to the particles passing through a rolling contact.

Severe sliding of steel components frequently produces particles having a blue, brown, or straw color. The colors are the result of localized heating producing the temper colors associated with steel. The severity of the wear and the attained temperature are indicated by the color of the particles, which change from straw to brown and then to blue color with the increase in temperature.

Cutting Wear: particles exist at the beginning of a component's life and in the failure stages. During the break-in period, the ridges on the wear surface are flattened and form cornices along the ridge peaks. These cornices subsequently break away in the form of long flat, curled-like particles. These particles at the failure stage are indicative of an active wear process. They are produced by penetration, ploughing, or cutting of one surface by another. This occurs by an intrinsic differential effect of a hard contaminant pressing into a softer surface, causing penetration of the opposing surface.

The particles produced by cutting wear are readily identifiable by their great similarity to machine chips or swarf but one much smaller. Cutting particles can range widely in length from as little as 5 microns to greater than 100 microns, with average widths of 2-15 microns. The particles also exhibit temper coloring resulting from heat during formation.

The presence of cutting wear particles is an indicative of abnormal wear situation and hence careful monitoring is required. Often some small individual cutting wear particles are found randomly dispersed within deposited debris and these in themselves do not indicate any adverse wear occurring. However, if the quantity and/or size of the particles increase with run time, then there are indications that a failure of a machine component is imminent.

Fatigue Wear: particles are produced in both gears and rolling contact bearings. There are five main types of fatigue particles. Normal fatigue and chunky fatigue are associated with gears whereas spherical, spall, and laminar particles belong to rolling contact bearings.

Gear Fatigue Particles: are produced in a gear system with a combination of rolling and sliding along the pitch line of the gear teeth; originating place of fatigue particles. These generally have smooth surfaces and are mostly irregularly shaped. The particles may have a major dimension to thickness ratio between 1:4 and 1:10 depending on the gear design. With increased wear, higher tensile stresses typically occur and fatigue cracks propagate deeper into the gear tooth producing fatigue chunks.

Rolling Fatigue Particles: The spherical particles associated with fatigue are generated in bearing fatigue cracks. When generated, their presence gives an early warning of impending trouble, as these are detectable before any actual spalling occurs. In many industrial systems, spalling of rolling bearings is preceded by the generation of large quantities of steel spheres that have diameters ranging between 1 and 10 microns. Fatigue of bearings has been estimated to generate several million spheres in the course of a failure.

Spall Fatigue Particles: constitute the actual material removed as a pit or spall opens up. These particles can reach a maximum size in excess of 1000 microns during the spalling process. Rapid failure can occur if incidences of spall become clear. These normally have very smooth surfaces, quite often displaying light scratching due to rotation and random irregularly shaped edges. The ability to recognize these particles is crucial, as the quantity of wear debris that results in a serious loss of performance is much lower for bearings compared to other machine components.
Laminar Fatigue Particles: are produced when wear particles pass through a narrow clearance of rolling contacts. This process produces ironing out of the particles into fairly large and very thin of up to 70 microns in major dimension with a thickness ratio of approximately 1:40. A property frequently displayed by these particles is the presence of holes, rounded or elongated, which allow the passage of transmitted light when viewed by a microscope. An increase in quantity of laminar particles, together with quantities of spheres is taken as an indication of the presence of rolling fatigue micro cracks, which in turn leads to spalling.
Non-ferrous Metallic Particles: The rotary particle depositor (RPD) deposits most types of non-ferrous metallic particles. The deposition of these particles is generally located in the outer rings because these are less magnetically susceptible compared to ferrous materials. The produced particles often have similar characteristics to those exhibited by ferrous particles. For example, the features found in rubbing, cutting, and sliding debris are often present. The major distinguishing feature of non-ferrous metallic particles is their color.
Non-metallic Particles: are also deposited by RPD. These particles are best shown by a comparison between transmitted and reflected light of the microscope. The particles can range from silica to fibres. Polymeric material and paint flakes can also be found [20].

IV. THE EXPERT SYSTEM

The procedure starts by collecting wear particle images from slides extracted from magnetic plugs or RPDs and are saved as a database. Figure 1 shows an image of expert systems interface that is programmed and developed by using Java computer programming language. The software package shows a combo box (left upper corner) that displays particle images from the database. Selections from six morphological attributes are shown as check boxes.
The operation of the expert system is based in the form of a dialogue between the user and the system. It is composed of queries and their corresponding explicit answers. Next are the attribute list and their corresponding answers in the form of a selection of a list of attributes options. Options selection is based on defined rules. For attributes of *size* and *thickness ratio* one option can be selected whereas for *shape, edge details, color,* and *texture,* one or two options can be selected.

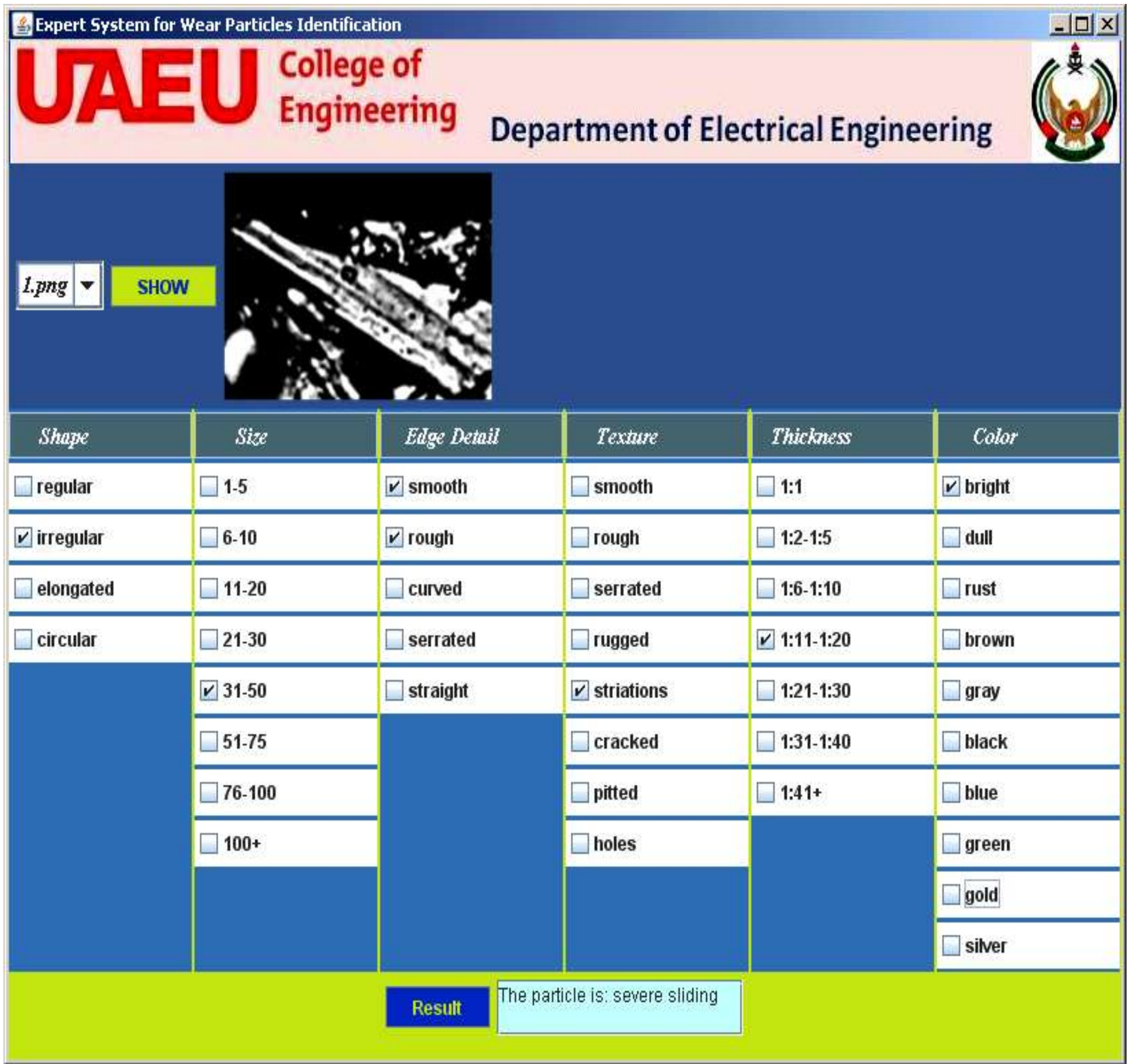

Fig. 1. Expert system software package

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TABLE I. WEAR PARTICLE IDENTIFICATION BASED ON MORPHOLOGICAL ATTRIBUTE PRIORITIES

Particle Type	Particle Attributes					
	size microns	shape	edge details	texture	color	thickness ratio
rubbing/pitting	<50	regular	smooth	smooth	bright dull	1:3-1:10
cutting	5-100	elongated	smooth curved	smooth rough	bright	1:21-1:30
severe sliding	26-50	irregular	smooth rough	striations	bright	1:11-1:20
normal gear fatigue	51-100	irregular	smooth cracked	smooth	bright	1:4-1:10
spherical rolling fatigue	1-10	irregular	smooth	cracked	bright	1:21-1:30
spalling rolling fatigue	approx. 900	irregular	rough	smooth	bright	1:21-1:30
laminar rolling fatigue	51-100	elongated irregular	rough	holes	bright	1:21-1:40
chunky gear fatigue	26-50	irregular	rough smooth	rough smooth	bright	1:2-1:5

Table I, shows few examples of wear particles with typical attribute options. After the features selection of all six attributes, the expert system window displays the conclusion of the selection, which results in the identified particle.

In some situations the individual features of the six attributes are not adequate to distinguish between some particle types, hence particle attribute priority gives each particle type a level of priority. This is crucial for identification since many particle types have some common attribute features. The priority knowledge is defined from 1st to nth priority, where n is the total number of attributes. Also, a 'nil' priority is included for the attributes priorities. This priority has no effect on the particle identification. For example, color attribute for rubbing is not in the list and therefore it has no role in the rubbing particle identification process.

Table II, shows some of the particles and their respective attribute priorities. It can be observed from the Table that the shape and texture attributes are important for ferrous particle types. However, color is an equally important attribute for all other types. Similarly, striation marks identify a particle as severe sliding which is the highest priority in the texture attribute. Attribute priority is also important reason being that some particle types have more than one option to describe the attribute. For example, the laminar rolling fatigue particle is more positively identified with both holes and cracks on the particle surface [21].

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Table III shows wear particle types and their appearances in machine wear systems. For example, rubbing wear particles are always in normal situations except when particle size starts increasing.

Particles from severe sliding wear appear sometimes however, such appearances can only happen in abnormal situations. Similarly, spalling rolling fatigue particles are rare in a system, nevertheless when it does appear then the system falls under active wear situation. Spherical RF particles appear sometimes and the quantity decides the normal or active situation, respectively.

TABLE II. EXAMPLES OF PARTICLE TYPES WITH ATTRIBUTE PRIORITIES

Particle Type	Attribute Priorities					
	1st	2nd	3rd	4th	5th	6th
rubbing/pitting	Sh	Sz	Ed	Tx	Tr	-
cutting	Sh	Sz	Tr	Co	Tx	-
severe sliding	Tx	Sh	Sz	Ed	Co	Tr
normal gear fatigue	Sh	Sz	Ed	Tr	Co	-
chunky gear fatigue	Tr	Tx	Sz	Sh	Co	-
spherical rolling fatigue	Sh	Tx	Sz	Co	-	-
spalling rolling fatigue	Sz	Tx	Sh	Co	-	-
laminar rolling fatigue	Sh	Tr	Tx	Co	-	-
Sh: Shape Sz: Size Ed: Edge Details Tx: Texture Co: Color Tr: Thickness Ratio						

TABLE III. EXAMPLES OF PARTICLE TYPES WITH THEIR APPEARANCES

Particle types	Particles appearance	Normal situation	Active situation
Rubbing	always	most cases	if size > 20 µm
Cutting	often	never happens	always
Severe Sliding	sometimes	never happens	always
Normal GF	sometimes	most cases	incr. in size & quant.
Chunky GF	sometimes	if less quantity	incr. in size & quant.
Spherical RF	sometimes	if less quantity	if high quantity
Spalling RF	rare	never happens	always
Laminar RF	sometimes	if less quantity	if high quantity

Knowledge extracted from above Tables help the system to conclude a decision. The particle identified shown in Fig. 1 is severe sliding. The particle shape is irregular as well as elongated. Size is approximately 40 microns. Its edges are overall smooth, and nonetheless there is some roughness at the corners. Surface texture that has the highest priority for severe sliding particle identifications clearly shows striation marks. The thickness ratio is appropriate for such particles and the color is bright.
Expert system is still in the learning stage where many of the attribute combinations are being added in the database. In future, more unidentified images will be added and identified to known particles.

V. CONCLUSION

The paper investigated the identification of microscopic particles generated by wear mechanisms using artificial intelligence techniques. Particles are classified using their visual and six morphological attributes to predict wear failure modes in engines and other machinery. The stages of processing are described in the paper, including an adept system to classify wear particles in terms of their six morphological attributes.

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