An Intelligent System for Machinery Wear Debris using Evolutionary Algorithms

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Abstract—Wear debris analysis is becoming an efficient method for machinery condition monitoring due to the recent development in image analysis techniques. It gives us information about not only the wear mode but also the wear mechanism of a machine component. Five types of debris are produced during the operation of a machine: Sphere, Platelet, Long-thin, Cutting and Chunky. A variety of parameters, related to the identification process of wear debris, can affect the performance of image analysis. This paper presents five numerical features to describe the boundary morphology of a debris. An ratio based methodology using Genetic Algorithms is used for classification. The experimental results indicate that due to the simplicity of proposed features, the classification of debris can be done quite rapidly and accurately.

Index Terms—Classification, Gearbox, Genetic Algorithm, Machinery Condition Monitoring, Numerical Descriptors, Wear Debris Analysis.

I. INTRODUCTION

Engineering systems require appropriate maintenance for productive and cost effective operation. These systems deteriorate with the passage of time which increases the need of proper monitoring and maintenance. To ensure continuous operation and long life of machinery, maintenance needs to be carried out before the actual occurrence of a fault in order to reduce the chances of total malfunction [1]–[3]. Fig. 1 shows how machinery degrades over time [2]. It consists of three stages: the run-in stage (I), the normal operation stage (II) and the failure stage (III). The initial and advanced damage is denoted by P1 and P2 respectively.

Machinery condition monitoring is widely used for predictive maintenance in many industries especially during the operation of sensitive and expensive machinery. It comprises fault diagnosis and prognosis to prevent a fault from developing into a catastrophic failure. By periodically obtaining data of key machine health indicators, the health of machine is determined and its remaining useful life is predicted. The overall productivity of a machine may increase due to the reduction in its downtime [4] [5].

Vibration and wear debris analysis are the two major techniques used to monitor the condition of a machine [2], [4], [6]–[9]. Vibration based monitoring measures the vibration of different mechanical parts of a machine and the measured signal is used to diagnose fault. This analysis is quite fast, can be conducted online and a number of software packages are available for automatic analysis of machinery faults. On the contrary, it only gives information about the condition of machine. Moreover, it cannot be used to diagnose faults in low speed machinery [5]–[8], [10].

Due to the recent advancement in image acquisition and processing techniques, wear debris analysis is becoming a much more effective practice for condition monitoring in industries as compared to vibration based monitoring [10]–[15]. Debris is generated due to friction among moving mechanical parts of the machine which is being carried in the lubricating oil. It is collected and analysed microscopically which gives comprehensive information about not only the condition of a machine but also the wear mode of the fault in a machine.

Five types of debris (sphere, chunky, long-thin, platelet, cutting curls) are generated during machine operation which are classified using their boundary morphology [1], [4], [10], [12], [16]–[18]. Fig. 2 shows the relationship among different

\[c4\] Text added.
\[c5\] Text added.

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It is useful to separate cutting debris from others. Fig. 8 demonstrates an image of a cutting debris.

C. Width Standard Deviation

Width standard deviation (WSD) measures the regularity of a wear debris. Fourteen points are calculated on the boundary of a debris image. The distance between the points is 1/14 times the length of the boundary vector. Considering the top left boundary point of the debris image to be our reference, the first point is at a distance of 1/14 times the length of the boundary vector in the clockwise direction from the reference point. Similarly, the fourteenth point is at same distance from the reference point but in the anti-clockwise direction. The distance between calculated points is obtained using two-point distance formula as shown in Fig. 3.

Width standard deviation is calculated by finding the standard deviation of the seven distances and dividing it by the length of the boundary vector. In this way, the feature is normalized for image of any size.

D. Edge and Shape Irregularity

The edge irregularity (EIR) and shape irregularity (SIR) of a debris image are the measure of its edge and shape uniformity. A regular debris will have smooth transition in X and Y coordinates of its boundary while an irregular one will have abrupt changes. By measuring these changes, a parameter for edge and shape irregularity can be determined. Fig. 4 shows two objects along with a plot of the coordinates of their boundary.

It is obvious from the plots that each distortion is representing a change in the ongoing trends of boundary coordinates. In order to determine a measure of edge irregularity, number of changes in trends that have more than 3 and less than 9 consecutive boundary coordinates, either X or Y, are calculated. Similarly for shape irregularity, number of changes in trend that have more than 9 consecutive boundary coordinates,
These features give a measure of the deformation of shape and are helpful in identifying chunky particles from other debris.

III. METHODOLOGY

A. Genetic Algorithm

Genetic Algorithms (GAs) belong to the class of Evolutionary Algorithms that are inspired from the process of biological evolution [21]–[24]. They are better suited for optimization problems involving local optima. These algorithms mimic the natural phenomena of random generation, crossover, mutation and selection to enable population of chromosomes get increasingly better at problem solving. It is suggested that if enough time is provided, the algorithms will result in a generation containing a chromosome that will provide an optimal solution to the given problem.

GAs can work even if we do not have the complete knowledge of cost function because they only require the evaluation of the objective function. Although they do not guarantee optimality, highly optimal solutions can still be obtained by adjusting the parameters involved in a GA. The use of crossover and mutation operators are extremely helpful in avoiding local optima and converging the solution to a global one. Due to these characteristics, GAs can be altered for a diverse range of applications from control system optimization to software creation, computer aided design, telecommunication and financial marketing.

1) Initialization: Genetic Algorithms work on a group of individuals. These individuals are randomly generated solutions of the objective function in a specified range and constitute the population. Total number of individuals is the population size. Every individual has two characteristics; its location called chromosome and its quality called fitness value.

2) Selection: The quality of each individual is measured using a fitness function. Based upon the fitness value, selection is done randomly to obtain a mating pool. Fitter individuals have more chances of survival as compared to other individuals. Selected individuals act as parents for the coming generation.

3) Crossover: Individuals selected in the mating pool crossover which results in a new generation of individuals known as offsprings. It can be one point or two point. The points are randomly selected for crossover. It is performed with a probability \( p_c \) and if crossover is not performed then the parents become the population of the next generation as it is. The value of \( p_c \) is normally high.

4) Mutation: Mutation is performed on the offsprings so that convergence of the population towards a local optimum can be avoided. It is performed with a probability \( p_m \). Normally the value of \( p_m \) is small to perform mutation occasionally. The point of mutation in a chromosome is also selected at random.

The variation operators are performed for a number of generations. A threshold is set either on number of generations or on error in converging population values. The will result in the global optimum of the objective function. GA is a stochastic process and there is a fair chance that the global optimum is
Every feature of all images in eq. 2 is divided by the corresponding feature in eq. 3 to obtain a matrix containing ratio of features, based upon which the classification will be done.

$$R_{ij} = \left( \frac{x_i(j)}{s_j} \right), \; i = 1, 2, ..., k; \; j = 1, 2, ..., 5 \tag{4}$$

A debris search is performed on the ratio matrix in eq. 4 using five functions. These functions contain the numeric ranges of each ratio which classify the input image into one of the five debris. GA is used to carry out the search. The use of GA helps in determining the class of debris by minimizing the error between five classes and the matrix $X$. These ranges are estimated by studying a collection of debris images and differ for every shape. Fig. 6 shows a flow chart depicting the whole classification process.

### IV. Experiment

In order to monitor the condition of a machinery and obtain wear debris samples, a pair of case hardened low carbon steel gears with a face width of 15mm and having 35 teeth was selected for gear pitting failure test. The gears were tested for 21 hours under high loading on a back to back gear rig as shown in Fig. 7.

Text added.
After every hour, wear debris bottle sampling was done. The bottle samples were further analyzed by using an imaging facility as shown in Fig. 7b. By using the screen capturing tool of windows on a real time camera display, the samples debris images were collected in a picture format. These images were taken as an input in MATLAB and Image Processing Toolbox \[25\] was used for further processing as described in section \[11\].

V. RESULTS

A total of 580 images were processed in MATLAB. It was observed during experiment that the testing conditions i.e. heavy loading and reduced face width of dear flanks caused a pitting failure due to surface fatigue. Due to this, most of the images were classified as Chunky. However, the proposed scheme was also tested against standard images of Sphere, Platelet and Cutting debris. A few samples are shown in Fig. 8. Nearly 86% of the images were classified correctly. This shows the accuracy of the proposed scheme. Moreover, due to the simplicity of the features and the classification technique, the total time taken for image processing, describing numerical features and classification of 580 images was 56 seconds. This is equivalent to a processing time of 0.097s per image. The classification results are shown in Table I.

![Sphere](image1.png) ![Platelet](image2.png)

![Chunky](image3.png) ![Cutting](image4.png)

Fig. 8: Samples of Debris Images

<table>
<thead>
<tr>
<th>Debris Type</th>
<th>Total Number of Images</th>
<th>Correctly Classified</th>
<th>Percentage Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sphere</td>
<td>183</td>
<td>162</td>
<td>88.5%</td>
</tr>
<tr>
<td>Platelet</td>
<td>54</td>
<td>44</td>
<td>81.4%</td>
</tr>
<tr>
<td>Chunky</td>
<td>267</td>
<td>233</td>
<td>87.2%</td>
</tr>
<tr>
<td>Cutting</td>
<td>76</td>
<td>63</td>
<td>82.8%</td>
</tr>
<tr>
<td>Total</td>
<td>580</td>
<td>502</td>
<td>86.5%</td>
</tr>
</tbody>
</table>

TABLE I: Classification Results

![Fig. 9: Aspect Ratio vs Roundness](image5.png)

![Fig. 10: Width Standard Deviation vs Roundness](image6.png)

Fig. 9 shows aspect ratio plotted against roundness. The graph shows that spheres have highest roundness and a low aspect ratio. Similarly, cutting particles have least roundness and highest value of aspect ratio. The values of aspect ratio for chunky and platelet are closer to that of sphere but the value of roundness is identical to that of spheres.

![Fig. 11 shape irregularity plotted against roundness.](image7.png)

Fig. 10 shows width standard deviation plotted against roundness. As it can be seen, sphere particles have highest width standard deviation while cutting have the lowest. Chunky and platelet have in between values of width standard deviation.

![Fig. 12 shape irregularity plotted against roundness.](image8.png)

Fig. 11 shows shape irregularity plotted against roundness. It can be seen that chunky particles have the highest value of edge and shape irregularity as compared to other particles. They can be distinguished quite clearly from others using this parameter.
Width standard deviation can be used to distinguish between cutting and other particles. Cutting particles have a small value of WSD while other particles have a larger value with spheres having the largest value due to their high roundness. Fig. 12 show the result of edge irregularity plotted against width standard deviation.

Although 2 parameter search utilizes minimum number of parameters but it may or may not be helpful in classifying the wear debris. A detailed discussion of 2 parameters search is mentioned in Table II. The analysis indicates that width standard deviation, edge irregularity and shape irregularity are those parameters that can be efficiently used to accurately classify wear debris.

Table II shows the classification results for the 3 parameters proposed in this dissertation. It can be easily seen that the search that involves shape irregularity and edge irregularity proves to be the one with the highest value of accuracy. Searches done using other parameters are accurate but are not good enough a compared to the one involving the parameters specified earlier.

**Fig. 11: Shape Irregularity vs Roundness**

**Fig. 12: Edge Irregularity vs Width Standard Deviation**

**Fig. 13: Width Standard Deviation vs Aspect Ratio vs Roundness**

**Table II: Classification using 2 Parameters**

<table>
<thead>
<tr>
<th>Numerical Parameters</th>
<th>Debris that can be accurately classified</th>
<th>Number of correctly classified images</th>
<th>Percentage Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>AS - R</td>
<td>Sphere, Chunky, Cutting</td>
<td>458</td>
<td>78%</td>
</tr>
<tr>
<td>WSD - R</td>
<td>Sphere, Chunky, Cutting</td>
<td>458</td>
<td>78%</td>
</tr>
<tr>
<td>EIR - R</td>
<td>Sphere, Platelet, Cutting</td>
<td>269</td>
<td>46%</td>
</tr>
<tr>
<td>SIR - R</td>
<td>Sphere, Chunky, Platelet, Cutting</td>
<td>502</td>
<td>86%</td>
</tr>
<tr>
<td>WSD - AS</td>
<td>Platelet, Sphere, Chunky</td>
<td>269</td>
<td>46%</td>
</tr>
<tr>
<td>EIR - AS</td>
<td>Cutting, Sphere, Chunky</td>
<td>458</td>
<td>78%</td>
</tr>
<tr>
<td>SIR - AS</td>
<td>Cutting</td>
<td>63</td>
<td>10%</td>
</tr>
<tr>
<td>EIR - WSD</td>
<td>Sphere, Cutting, Chunky</td>
<td>458</td>
<td>78%</td>
</tr>
<tr>
<td>SIR - WSD</td>
<td>Sphere, Platelet, Chunky, Cutting</td>
<td>502</td>
<td>86%</td>
</tr>
<tr>
<td>SIR - EIR</td>
<td>Chunky</td>
<td>233</td>
<td>40%</td>
</tr>
</tbody>
</table>
VI. Conclusion

This paper aims to address the problem of accurate classification of wear debris. Five features of debris images are presented that are simple to categorize them. A ratio based methodology is used for classification that uses ranges of features to identify the specified wear particles. The proposed method is tested on a number of debris images and the results show the validity of proposed features and classification technique.

References


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</tr>
</thead>
<tbody>
<tr>
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<td>Sphere, Chunky, Cutting</td>
<td>458</td>
<td>78%</td>
</tr>
<tr>
<td>EIR - AS - R</td>
<td>Sphere, Platelet, Cutting</td>
<td>502</td>
<td>86%</td>
</tr>
<tr>
<td>SIR - AS - R</td>
<td>Sphere, Platelet, Cutting</td>
<td>502</td>
<td>86%</td>
</tr>
<tr>
<td>SIR - EIR - WSD</td>
<td>Sphere, Chunky, Platelet, Cutting</td>
<td>502</td>
<td>86%</td>
</tr>
</tbody>
</table>

TABLE III: Classification using 3 Parameters