EFFECT OF LUBRICANT ON WEAR DEBRIS COLOR DIAGNOSIS

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ABSTRACT

Color feature of debris is quite often used for source diagnosis in machine component while performing wear debris analysis (WDA). This feature is commonly observed and analyzed with different offline debris imaging setups. In these setups, its attributes remain consistent in their values as just a colorless medium i.e. air is in between the imaging setup and the observed debris. But in the case of an online debris analysis, the measurements of these attributes can be affected as the imaging has to perform in the presence of a machine lubricant. The lubricant color can affect the measurement of debris original color attributes and further can cause a wrong source diagnosis. In this paper, the effects of lubricant color on debris color measurements are discussed. A debris imaging setup is used for experimentation. Micro size steel debris are analyzed with three different lubricants. The debris color measurements are initially performed in an offline mode when the debris are placed on a glass slide. Later the mentioned measurements are taken in the presence of lubricants when the debris are flowing with the lubricant medium via a flow cell. Finally a comparison is made which concludes that the darker the lubricant the lesser will be chances to deduce the material (color and attributes). Whereas brighter lubricants do not hinder the analysis and identification of material and hence are considered suitable for qualitative wear debris analysis.

KEYWORDS*: Wear debris analysis; Image processing; Color based diagnosis*

1.0 INTRODUCTION

The research world probed into "Wear Debris Material Diagnosis" in the mid-70s (Pocock et al., 1979; Stachowiak and Podsiadlo, 2006). Most of the academic researchers conducted computer based analysis to classify the type and mode of debris wear (Khan et al., 2008; Laghari et al., 2010; Lunt, 2011; Podsiadlo and Stachowiak, 2005; Xu et al., 1997). These efforts utilized the offline techniques of image processing, artificial intelligence, mathematical and statistical rules and smart

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sensing methodologies (Cao and Xie, 2007; Iwai et al., 2007; Odi-owei et al., 1976). The prior studies were extensively comprised of debris features such as its color, shape, quantity, size and distribution. However, the subject of lubricant properties and its effect on debris analysis also demands a signficant importance. Specially, the effect of lubricant color in diagnosis based on image processing (Hu et al., 2007; Peng, 2001; Tonghai et al., 2009).

A system was required to analyze the effect of lubricant color on wear debris. A system capable of demonstrating the effect(s) of color on debris image and analyzing results. The two basic requirements for such a system are:

(i) Experimental setup for online debris imaging.
(ii) Software code for processing the captured debris images and providing the correct color attributes for analysis.

2.0 EXPERIMENTAL SETUP AND DETAILS

The above mentioned requirements were developed under the presented work. The complete experimental setup is divided in two main components:

(i) Debris imaging hardware
(ii) Software code for image data analysis (Code in Matlab©)

The hardware set-up consists of a Perspex flow frame, a lubricant dosing pump, an optical microscope with a tungsten light source, a charge-coupled device (CCD) camera with a USB output and soft tubing. During the diagnostics the dosing fluid pump extracts the lubricant from the lubricant sump and directs it towards the inlet port of the flow frame. The design of the flow frame, as described in section 2.1, allows the lubricant to flow through a thin flow path, hence allowing the debris present in the lubricant to be easily focused by using a simple optical microscope. A microscope and CCD camera with its USB output is used that shows the microscopic focused image on a PC screen in real time. By using a PC screen capture tool, the observed debris can be saved as an image file. The developed Matlab© based image data analysis software is capable of using and analyzing the saved image for further color diagnosis. The whole methodology schematic is shown in Figure 1.

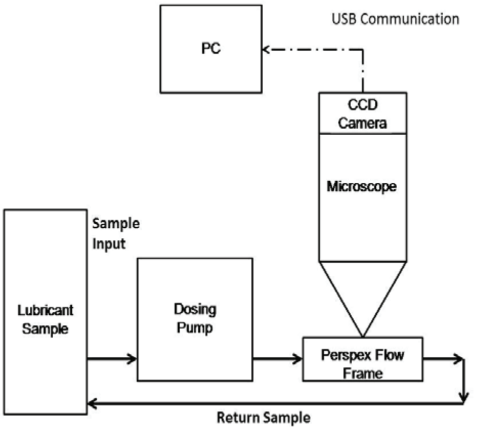

Figure 1. Online working schematic of hardware setup

2.1 Flow frame construction and working

The Perspex flow frame is a rectangular frame consisting of three main components, i.e. lubricant flow bed, imaging window, and flow path gasket. During experimentation the lubricant containing debris is pumped into the Perspex flow frame through its inlet port. The design of the frame allows the lubricant to flow between the imaging window and the flow bed with a fluid thickness equal to the flow path gasket. The currently used gasket has a thickness of 300 µm. Flow frame with its basic components are shown in Figure 2.

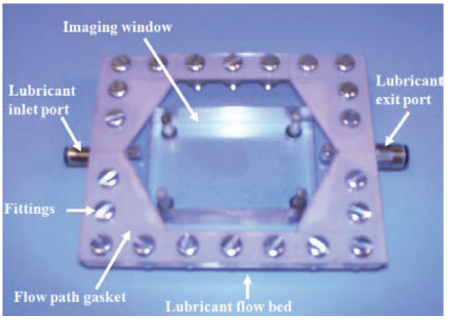

Figure 2. Prespex flow frame

2.2 Software for debris image capturing and processing

Hardware setup provides information of debris images in the form of numeric values. A software setup is used for the analysis of raw data into representable form. It has been formulated in MATLAB® for near real time functionality. The software captures the debris image from the live video of lubricant using the MATLAB image acquisition toolbox. It further creates its RGB (Red, Green, and Blue) color map and export it to the MATLAB workspace for color analysis. The flow diagram of the software functionality is provided in Figure 3.

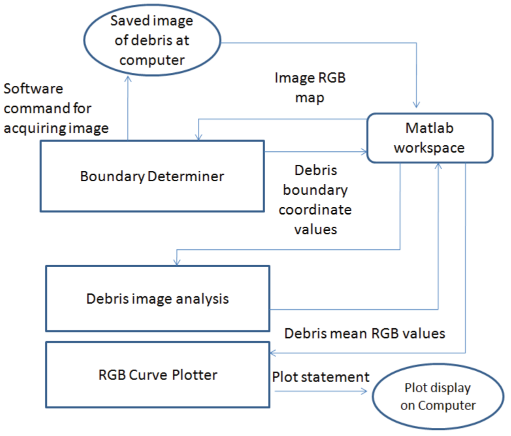

Figure 3. Flow diagram of software with its main components

The "Boundary Determiner" component, as shown in Figure 3, detects the possible boundary coordinates of the observed debris from its image. This detection is based on a sequential learning algorithm (SLA) which is inlined with a principle assumption i.e. an object (debris) can only be visualized if and only if the object color attributes are different from its background color attributes, otherwise it can't be distinguish.

The algorithm generated for this purpose reads the entire image size i.e lubricant plus debris, and takes its RGB value at each pixel position. It then subtracts the RGB value of a lower pixel position from a higher pixel position separately for R, G and B. It analyzes the results obtained and if the difference is greater than or equal to 3.5 then the first pixel point giving such a value would be the starting coordinate of the boundary of a particular debris. Similarly, the last pixel point giving a difference of RGB value of more than 3.5 would be the closing coordinates of the boundary. The value '3.5' was obtained by a series of empirical tests and dependent on the hardware setup.

After marking the debris boundary coordinates, the mean RGB values are calculated by using the'mean' statement and later plotted by the 'plot' statement of the Matlab©. Finally, a graph is obtained that shows the trend of the mean RGB value during a test.

2.3 Lubricant and debris samples

In order to study the effect of lubricant color on wear debris material diagnosis, three lubricants of different color were selected. The details are given in Table 1.

Table 1. Properties of selected lubricants

Properties	ATF 200	Caltex Motorcycle oil	Shell Mobil Oil
Viscosity at 100 C^0	7.9	10.1	7.1
Flash point C^0	218	> 200	>200
Pour Point C^0	-42	-35	-15

Steel was selected as the sample debris material. Debris were obtained by the abrasive filing on a steel plate at the fabrication lab. The sample of collected debris is shown in Figure 4.

Figure 4. Steel wear debris

3.0 TESTS AND OBSERVATIONS

3.1 Perliminary dry test

Preliminary test was performed on the steel debris sample in the absence of lubricant. The steel debris was placed under the microscope and captured with the help of a CCD camera. The algorithm generated in Matlab was run over the steel debris images. Mean RGB values of were determined and plotted as shown in Figure (5).

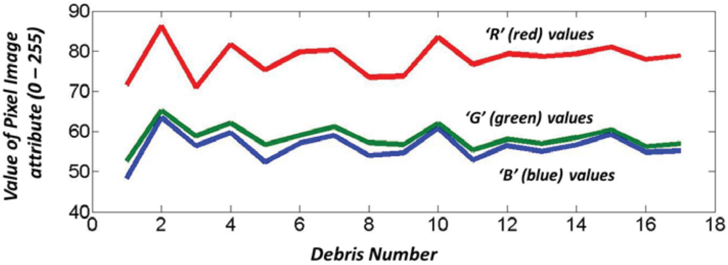

Figure 5. Measured RGB values without the presence of lubricant

A total of 17 debris were used to measure the RGB attributes of the selected steel debris. A distinguish high value of 'R' was observed as shown in Figure (5). The observed mean values of 'R', 'G' and 'B' were 76, 58 and 56 respectively.

3.2 Test with lubricant sample 1

Test 1 was performed with lubricant sample 1. 100 ml of this sample with a small of quantity of Steel debris was pumped into the experimental setup. The rate of the flow was controlled by the dosing pump and the images of the debris were captured. A total of 17 debris images were captured, processed and analyzed with the help of Matlab code. An image of a debris that was captured and outlined for RGB measurements during the test is shown in Figure 6. The obtained RGB values of the 17 debris were plotted as shown in Figure 7.

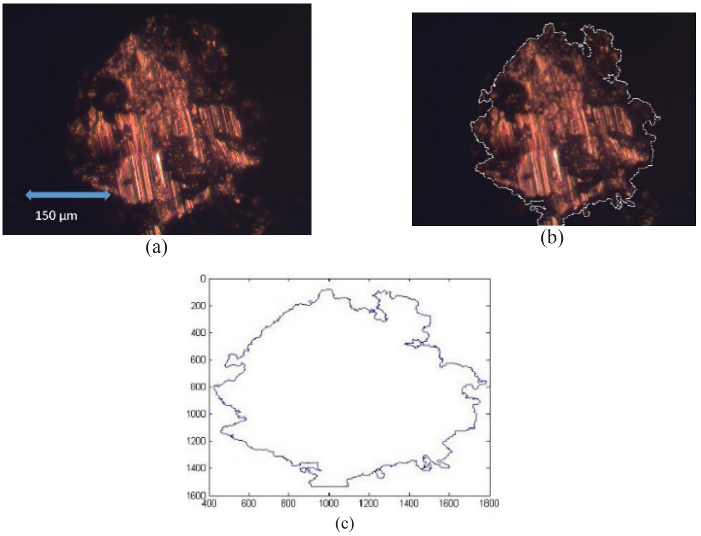

Figure 6. Debris image and processing with lubricant sample 1 (a) Raw debris image, (b) Debris with software sketched boundary and (c) Extracted boundary for RGB values measurement

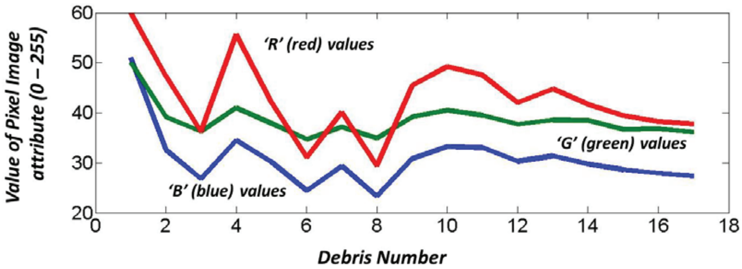

Figure 7. Debris image and processing with lubricant sample 1

The graph Figure 7 shows low values of 'R' which in comparison with Steel debris graph Figure 5 is contradictory. Hence when steel is in lubricant sample 1, the Matlab code does not identify it as 'steel'.

3.3 Test with lubricant sample 2

Test 2 was performed with lubricant sample 2. A total of 12 debris images were captured, processed and analyzed. An image of a debris that was captured and outlined for RGB measurements in this test is shown in Figure 8. The obtained RGB values of the 12 debris were plotted as shown in Figure 9.

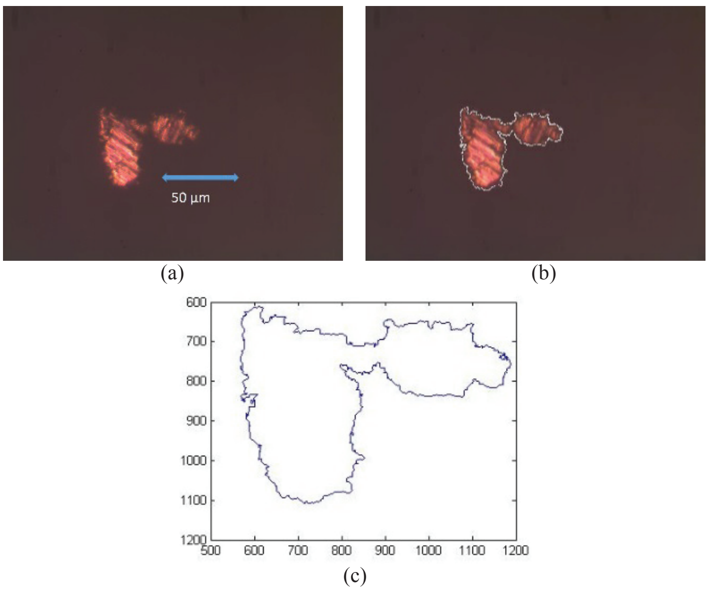

Figure 8. Debris image and processing with lubricant sample 2 (a) Raw debris image, (b) Debris with software sketched boundary and (c) Extracted boundary for RGB values measurement

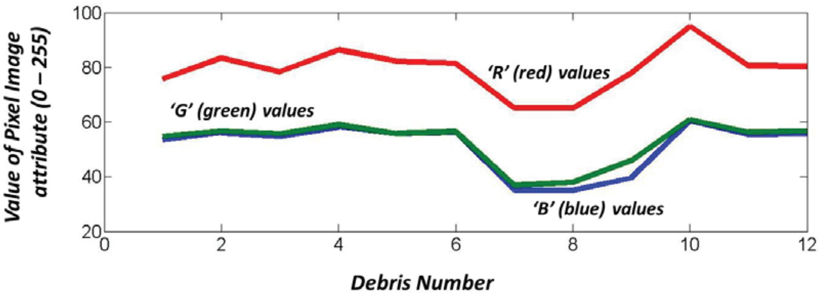

Figure 9. Debris image and processing with lubricant sample 2

The above graph (Figure 9) when compared with steel debris graph (Figure 5) gives a similar pattern of RGB values. Thus can be concluded that when in lubricant sample 2, steel debris retains its color and attributes.

3.4 Test with lubricant sample 3

Test 3 was performed with lubricant sample 3. A total of 15 debris images were captured, processed and analyzed. An image of a debris that was captured and outlined for RGB measurements during this test is shown in Figure 10. The obtained RGB values of the 15 debris were plotted as shown in Figure 11.

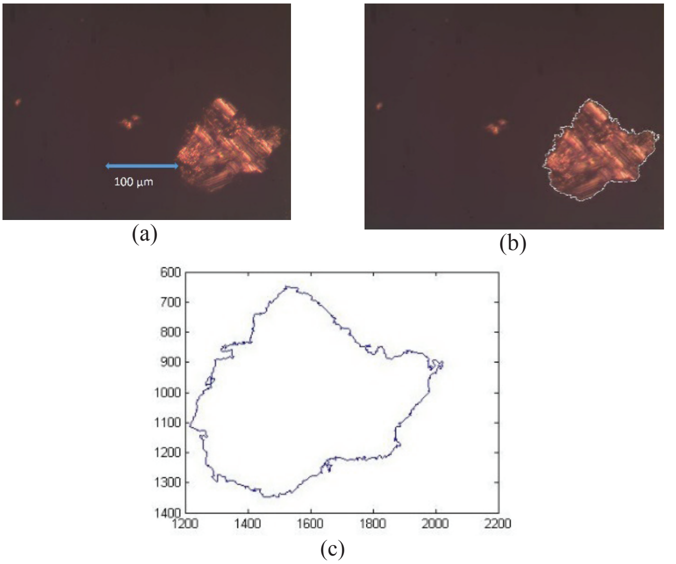

Figure 10. Debris image and processing with lubricant sample 3 (a) Raw debris image, (b) Debris with software sketched boundary and (c) Extracted boundary for RGB values measurement

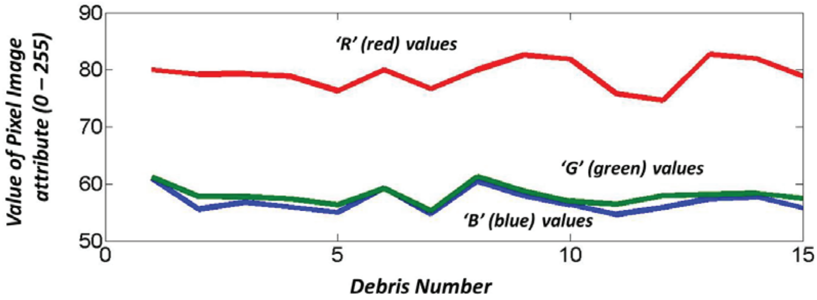

Figure 11. Debris image and processing with lubricant sample 3

Comparison of the graph for lubricant sample 3 (Figure 11) with steel debris (Figure 5) gives a similar trend as lubricant sample 2.

3.5 Observations

The variations in the above plotted graphs give an idea about the effect of lubricant color on mean RGB values of debris. As per Figure 7, lubricant sample 1 contains meanvalue of 'R' (red) less than 50 for almost 95% of debris samples. However, lubricant sample 2 and lubricant sample 3 have no such impact. The plots above show a pattern for lubricant sample 2 and lubricant sample 3 as they both contain higher values of 'R' as compare to their respective 'B' and 'G' values. This relation actually provides a brighter impact in the debris image as compare to debris of lubricant sample 1. That actually verifies the dark nature of lubricant sample 1.

4.0 CONCLUSION

Effect of lubricant color imparts a significant role on wear debris analysis specially when the lubricant is dark in color. Steel debris in all three lubricants and its relative values of RGB shows the the impact of lubricant color. By comparing Figure 5 with Figures 7, 9, and 11, it shows the RGB of steel debris does really change by using a lubricant of dark color.

Analyzing the effect of lubricant color on wear debris provides a new dimension in image processing techniques. The above work can be extended and will be firmly validated if the analysis will be performed by using debris sample of different materials.

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