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CHARACTERIZATION OF WEAR IN IMAGES OF SAMPLES FROM THE HFRR TEST

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Abstract. *Lubricity is an important characteristic for the evaluation of lubricating fluids, standardized by standard and measured by the HFRR (High Frequency Reciprocating Rig) test, which is given by the sphere-disc tribological system in lubricated contact, and it produces as a result, images from the wear and the scar diameter is extracted, defining the Wear Scar Diameter - WSD. From a set of samples of different fuels applied as lubricants, images of the worn surfaces were obtained. Thus, it is proposed in this work to explore other characteristics of the images in addition to the WSD, thus allowing a better description of wear and the type of lubricant used. With the images acquired in the lubricity test, image processing techniques were applied using the Matlab software and the OpenCV library to obtain quantitative parameters. From this information, an Artificial Neural Network was able to classify new images according to the type of fuel used in the test with an average accuracy of 75%, demonstrating the use of artificial intelligence to identify and classify wear patterns from the analysis of their images.*

Keywords: *wear, image processing, tribology, lubricity, Artificial Neural Networks*

1. INTRODUCTION

The images of worn surfaces are important resources in understanding the phenomena involved in the wear process. A surface fractured by fatigue, for example, registers a characteristic sign, called “beach marks”, identifying the crack propagation process for this effort (Budynas and Nisbett, 2011).

Mikołajczyk et al. (2017) used the images of edges of turning tools surfaces to predict their useful life. Klein et al. (2013) investigated bearing defects using image processing techniques.

Tribological systems evaluate the wear mechanisms that occur in contact between metals and the lubricity of fluids. The objective of these systems is to reproduce the wear mechanism under specific conditions of load, speed, temperature and environment, as in the Pin on Disc and Ball on Disc tribometers (Pantaleón et al., 2012). Wear in diesel engines, for example, can occur due to excessive friction that reduces the life of engine components, such as pumps and injection nozzles, whose failure is attributed to the lack of lubrication in the fuel, this property being known as lubricity (Farias et al., 2015).

The criteria established to standardize the wear conditions of a ball-on-disc test are defined by the ISO 12156 standard, which is a test for defining the lubricity of fluids. The test in question uses the HFRR equipment. The HFRR (High Frequency Reciprocating Rig) test measures the level of wear and fuel lubricity through the wear of a ball rubbed on a flat surface. This test is evaluated through the parameter Wear Scar Diameter (WSD), being a measure obtained from a 2D image. However, this measure is limited to analyzing the geometry of the image (Gevorgyan et al., 2017).

The HFRR images show structural similarities with images of melanomas, an area of medicine in which several studies on classification between benign and malignant are found. The use of images for characterization of skin cancer has motivated the development of works that use artificial intelligence to replace imprecise diagnoses, due to the limitations of human operations to determine the malignancy or not of a melanoma (Barros, 2018). In addition to the medical area, artificial intelligence also presents itself as a solution to engineering problems. Liu et al. (2018) cited that one of the ways used to detect bearing failures is through the use of artificial intelligence in order to recognize wear patterns.

The literature presents nine descriptors extracted from melanoma images for classification through an ANN (Artificial Neural Network): diameter, symmetry (x-axis and y-axis), mean of colors (channels R, G and B), color variance (channels R, G and B) (Barros, 2018). The proposal is to use these descriptors to classify two groups of samples from the HFRR test, and verify if the properties of combustible fluids can be interpreted by images of the worn surfaces. An ANN was created to learn how to make the classification using these nine criteria. The results obtained indicate 75% accuracy.

2. METODOLOGY

From a group of 56 images (Farias et al., 2015) image processing techniques were applied using the Matlab image toolbox and the OpenCV library. Half of the samples were tested using a soy oil based fluid and the other half sunflower oil.

2.1 HFRR

Over time, and the evolution of fuels, it was noticed that the continuous reduction of sulfur in diesel fuel resulted in low fuel lubrication and engine pump failure, a fact that led to the development of a series of methods that measure the level of the fuel lubricity. However, measuring lubricity is expensive and time-consuming, and several predictive models have been developed in the past, based primarily on various fuel properties (Korres et al., 2002).

The HFRR test is standardized by ISO 12156 to assess the lubrication property of diesel fuels, including those that may contain a lubrication-enhancing additive (ISO, 2018).

The rising cost of oil and the demand to reduce carbon dioxide in the atmosphere are driving the search for alternative fuels to gasoline. Therefore, gasoline fuels are blended with alcohol to reduce the fossil energy content. However, the addition of new substances tends to change fuel properties, including the lubricity item (Gevorgyan et al., 2017).

The Figure 1 illustrates the bench components of the HFRR lubricity test. The image on the right is obtained through an optical microscope, indicating the region worn by friction. The average of the x and y diameter measurements represents the WSD.

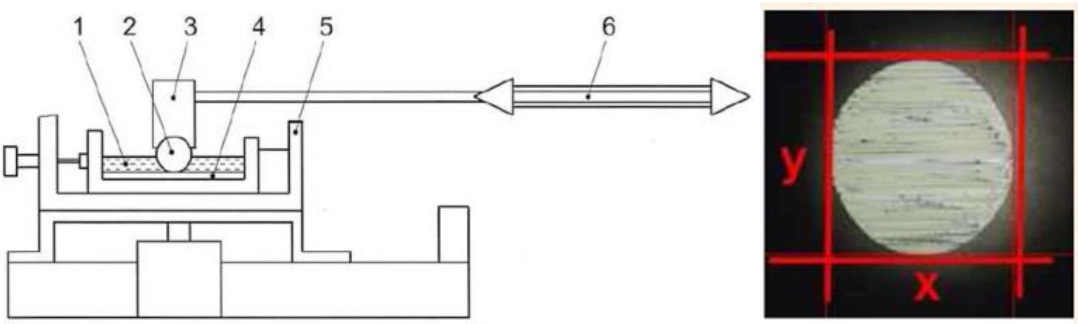

Figure 1. HFRR equipment on the left: 1) fluid reservoir; 2) test ball; 3) test mass; 4) test disk; 5) heating bath; 6) oscillating movement. Wear sore on the ball on the right.

In addition to the WSD parameter, the lubricity test with the HFRR also makes it possible to obtain data on the coefficient of friction, percentage of interfacial lubricant film, temperature and temperature (Farias et al., 2015).

2.2 Diameter

Applying the Hough Transform to detect circles, the circumference that best approximated the wear scar was obtained. From it, the diameter and geometric center were obtained. The Figure 2 shows the circle constructed using the Hough Transform. Together with the drawing, the diameter value in pixels is obtained.

Figure 2. Circle identification by the Hough Transform.

The conversion to the units of measure of the samples was not made since the complete matrix, with all diameters, was normalized, becoming dimensionless.

Barros (2018) uses Matlab's minEnclosingCircle function. However, this was not adequate to identify a single homogeneous region and surround it. Therefore, we adopted OpenCV's cv2.HoughCircles function to construct the circle, and thus extract the value of its diameter.

2.3 Symmetry

For the symmetry criterion, the images were segmented and divided into four quadrants from the geometric center. The difference between the total number of filled pixels generated the descriptors of symmetry in relation to the vertical and horizontal axes, according to Figure 3.

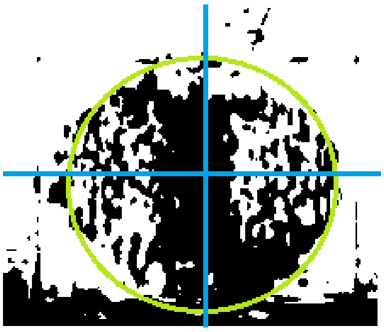

Figure 3. Image thresholded and divided into quadrants.

2.4 Color mean and variance

As for the means and color variance, histograms were obtained in channels R (red), G (green) and B (blue). Then, mean and variance of each data set were obtained, according to Figure 4.

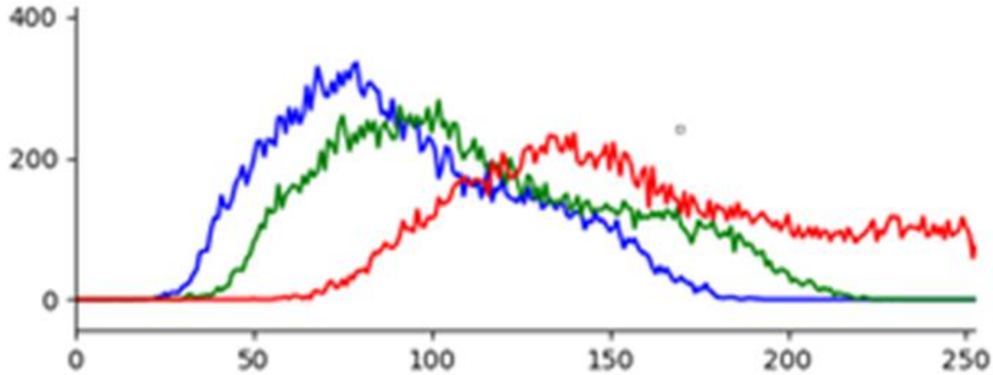

Figure 4. Histogram on channels R (red line), G (green line) and B (blue line).

With the data from the histogram matrices of each channel, arithmetic calculations were applied to normalize the values and obtain the means and variances.

2.5 Artificial Neural Network

An ANN was built to verify the efficiency of the descriptors in characterizing the group of samples. The descriptors used for learning the network are listed in Table 1.

Table 1. Definition of ANN entries.

Descriptor	Characteristc
1	Diameter
2	Red channel mean
3	Green channel mean
4	Blue channel mean
5	Red channel variance
6	Green channel variance
7	Blue channel variance
8	x-axis asymmetry
9	y-axis asymmetry

A Feed Forward Back Propagation network was built with an input layer (descriptor data), two intermediate layers (one with 60 neurons and the other with 1 neuron) and an output layer (with two qualitative values), according to Figure 5. The transfer function is hyperbolic tangent.

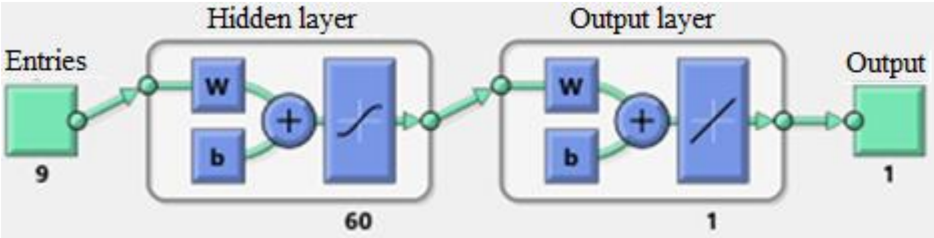

Figure 5. Network Feedforward.

The networks were built in Matlab software. The selection of inputs, target and architecture were carried out in the execution of the nntool toolbox.

The parameters “w” and “b” correspond to the synaptic weight and bias, respectively, found by the network in the intermediate layer. The output corresponds to the target result, -1 or 1, depending on the groups being compared.

As for the network training parameters, for all cases the stopping criterion was the number of epochs (1000), with a maximum error of 10^{-7}, learning rate of 0.01 and unlimited simulation time .

Once the network was trained, the validation step followed. The second group of images, of the two types of lubricants, was used to serve as inputs to the network. In this case, the objective is no longer to define the synaptic weights, but through the already determined weights to be able to classify which type of target fits.

The proposal is to maintain a proportion of 70% of the images for the network training stage and 30% for validation. For each image added, the corresponding target was defined, with the value "-1" for a certain type of fuel and "1" for another type of lubricant. In this way, the network will define the necessary synaptic weights to associate each entry with its related target.

3. RESULTS AND DISCUSSION

The images were divided according to the type of biodiesel: soy and sunflower. Each group has 28 samples, 20 for training and eight for validation. The network presented a performance of 90% of correct answers when applying the input matrix. In the case of the validation matrix, the total number of correct answers was 75%, as shown in Figure 6.

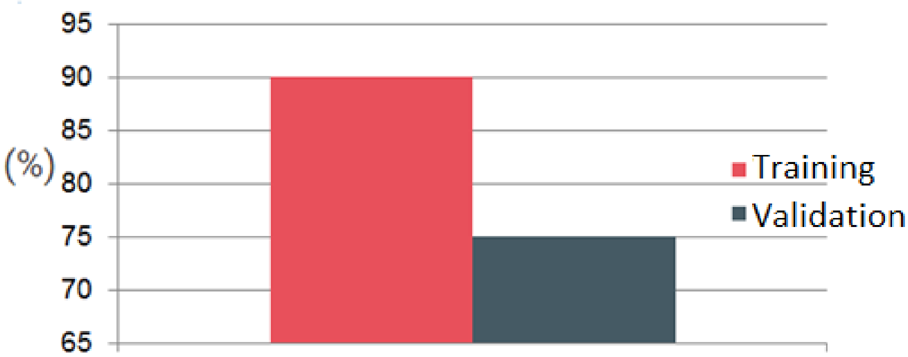

Figure 6. Accuracy in the training and validation steps.

The absence of studies similar to this one makes it difficult to compare the results. But because of the similarity with the melanoma works, it is possible to confront them. Barros (2018), whose work is more similar to this one, obtained an RNA that classified malignant and benign melanomas with 90% correct answers.

Wadhawan et al. (2011) achieved an efficiency of 71.31%, using histograms and an SVM algorithm, a result close to that of this work. Mustafa et al. (2017), also used the SVM, but with an ABCD Rule approach, obtaining 80%.

Abuzaghleh et al. (2014) expanded the classification groups, dividing the images into benign, malignant and atypical lesions, measuring a classification efficiency for each group of 65%, 55% and 70%, respectively.

4. CONCLUSIONS

Tribological assays such as HFRR are especially interesting for image processing analysis as they are standardized by the norm, allowing process repeatability under the same conditions. In the case of the studied samples, the variability of the images came from the choice of fuel used in the lubricant function.

To identify this variability, we sought to define evaluation criteria for these images in order to recognize patterns for each group of samples. The similarity between wear sores with melanoma images allowed the descriptors used in studies on melanoma classification to be applied in the tribological context. Melanoma diameter is directly associated with the concept of WSD, a lubricity gauge. The use of the Hough Transform for detecting circles can even serve to replace the manual measurement of the mean diameter, which is subject to operating errors. Similarly, descriptors associated with color can provide characteristics about fuel composition and oxidation conditions. Asymmetry can also be applied to wear sores as they reflect different concentrations of wear.

The descriptors were then evaluated using an ANN. The samples were correctly classified according to the composition of the base fuel (soybean or sunflower), with an accuracy of 75%.

In addition to presenting descriptors that characterize the lubricity test samples and providing a fuel classifier, the work contributes to a greater integration between the tribological sciences and the areas of computer vision and artificial intelligence, which are essential to solve the challenges of current science.

In order to improve the characterization capacity of the samples, it would be interesting to apply the proposed methods to a larger group of images, given that the learning of the network is greater according to the amount of information used in the training. You can also search for new descriptors for the images, in order to expand the classification groups. One proposal is the specific study of cracks in wear sore, which are associated with abrasive wear. In addition, a specific parameter for the eccentricity of the bedsores can be searched, since they are approximated to a circumference to obtain the diameter, which generates an intrinsic error.

Just as the HFRR operates under standardized conditions, differentiating the type of combustible fluid, other physical properties (such as lubricant temperature, applied load and speed) can be varied and their effects on wear sore studied. Once a database has been built with the predominance of different wear mechanisms, it is possible to analyze bearing surfaces at the end of their useful life, in which ANN can diagnose which mechanisms contributed most to the wear of the part, in order to avoid it.

Similarly, by grouping the images according to the most active wear mechanism, descriptors can be used to establish acceptance thresholds, determining normal ranges of action for certain fuels.

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