Towards a quantitative characterization of wear particles using image analysis and machine learning

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ABSTRACT

The current work proposes to move towards a quantitative characterization through advanced image processing. Four steps are followed: pin-on-disk experiments (to generate third body), image acquisition of third body particles, image processing, and extraction of quantitative characteristics of third body particles.

Keywords: Tribology, image processing, machine learning.

1. INTRODUCTION

Tribology was theorized in 1966 by Peter Jost[1]. It includes various aspects such as the study of friction, wear and lubrication. The work presented here revolves around the first two aspects, to which we must add another concept introduced by Maurice Godet [2,3] : the third body. This concept which makes it possible to apprehend friction and wear problems no longer as volume and surface problems but as interface problems, i.e. the volume of material that separates the bodies in contact while accommodating most of their difference in speed. Later this problem of wear will be reformulated by Berthier in the form of the tribological circuit which describes the flows of the interfacial layer in a sliding contact [4].

To study wear and its mechanisms it is necessary to study the flows of third body and more particularly the flow of ejected wear particles[5,6]. These studies generally consist in a qualitative study of wear, through an estimate of severity, type or source. The objective of this study is to quantitatively correlate third body flows to experimental rheological values specific to friction tests such as the evolution of friction coefficient. For this purpose a serie of sliding tests is conducted on a pin on disk tribometer.

2. EXPERIMENTAL METHOD

A tribometer of type pin on disc is composed of a fixed pin in contact with a rotating disc, the rubbing parts of the mechanism are composed of 35CrNiMo16 (Euronorm) steel and will allow the production of third body.

During a test it is possible to pilot several parameters that may have an impact on the morphology of the third body, such as the linear speed, the friction distance or the atmosphere in which the contact is plunged.

Tribological data are acquired in situ, as the tangential force using an S-type force sensor. It is also possible to evaluate the vibrations with a 3-axis accelerometer and to monitor the progress of the test by positioning 2 cameras in contact input and output. An example of these in situ measurements is given in Figure 1. In the future it is envisaged to add a microphone to record the sounds that may occur during the test.

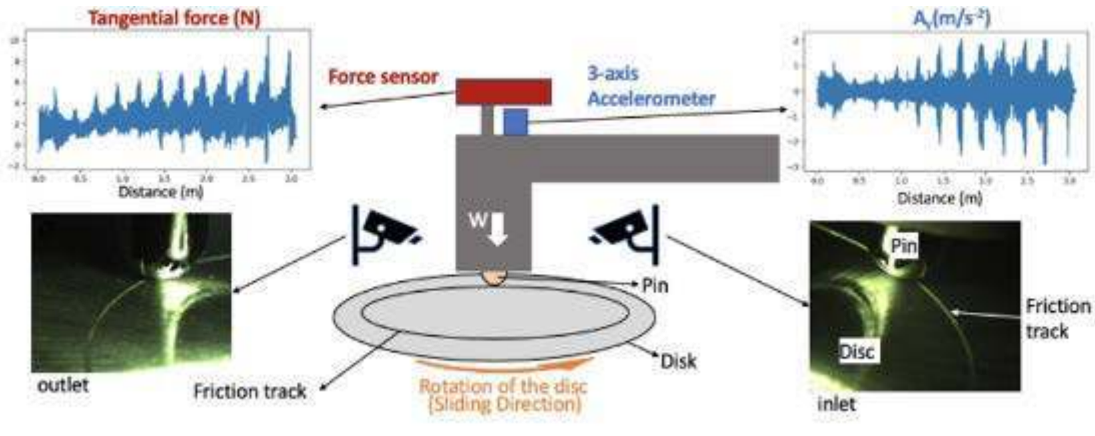

Figure 1 : Tribometer and measurement

Once the tests are completed, the experimental data must be studied, this requires an evaluation of the instantaneous coefficient of friction

$$COF = \frac{Tangential\ Force}{Normal\ Force}$$

It is also possible to calculate its average evolution per lap.

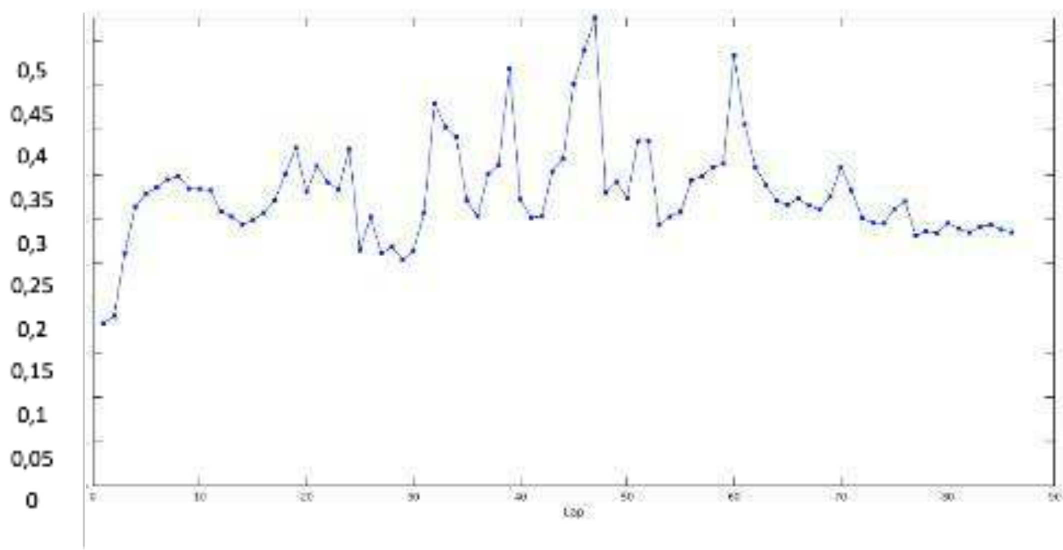

Figure 2 : Average friction per lap

This same type of analysis is performed on the accelerometer data and can be correlated with tangential force values.

Post-mortem analysis is performed after tests through the acquisition of images with a scanning electron microscope [7]. For this the contact is open, it is then possible to observe the track on the disk, and the pin.

Figure 2 shows an example of a trace on pin (a) and disk (b).

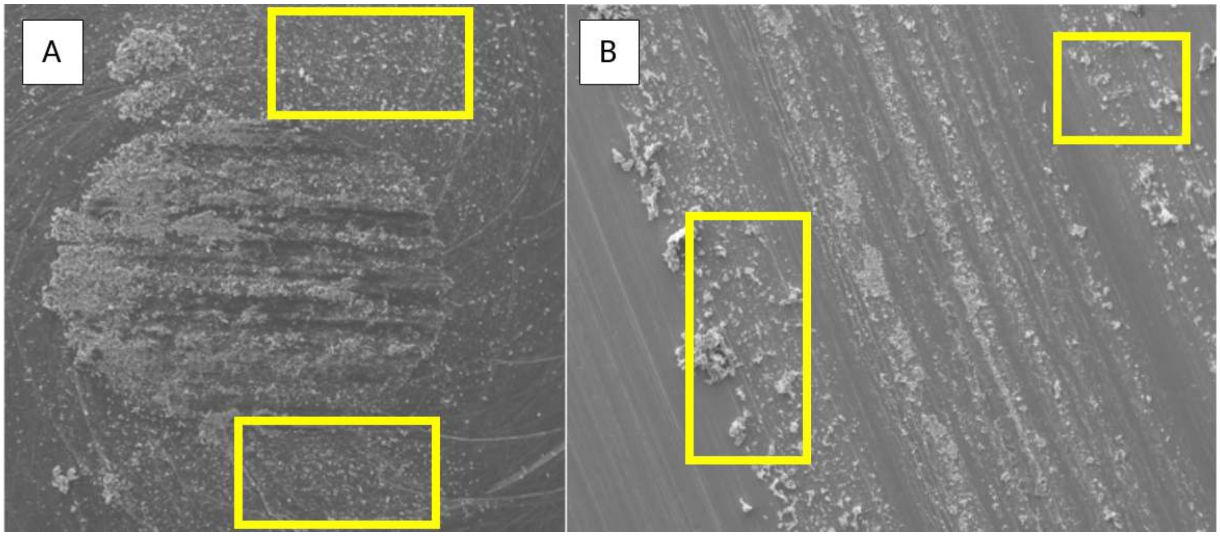

Figure 3 : Fiction track on Pin (A) and disc (A)

It is however essential to keep in mind that the track on the disc corresponds to the last lap of the test, so it will be impossible to trace back to an event that occurred upstream, there may be traces but it is impossible to identify them clearly.

This phase of image acquisition also makes it possible to search for recurring patterns, the formation of third body agglomerates or to observe a certain regularity in the textures, which can make the link with the tribological data processed rather.

In this work, we are mainly interested in wear particles, thus the particles ejected from the contact, in yellow on figure 2. It is the study of the characteristics of these particles that will allow to trace back to the conditions of wear that occurred during the life of the contact.

3. IMAGE PROCESSING

Once the images of particles are acquired, they must be segmented in order to extract geometric, morphological and topological characteristics [8,9,10,11], these characteristics will provide information on the type of wear in the contact.

To segment the images a python code is developed, it allows to perform different operations on the images, such as the application of smoothing filters, changes in exposure or contrast, or different operations on the histogram. At the end of these processes an automatic Otsu thresholding is carried out.

After segmentation there are imperfections such as holes in the segmented regions as well as very small artifact-like regions. Thanks to morphological geodesic operations it is possible to clean the images of these imperfections.

See left side of flowchart (Fig3).

As indicated in the previous section, by modifying the experimental conditions the morphology of the third body is modified, so a particle with a powdery appearance cannot be satisfactorily segmented by thresholding. Dark areas or areas with texture / topography will generally be interpreted as holes (Fig 4).

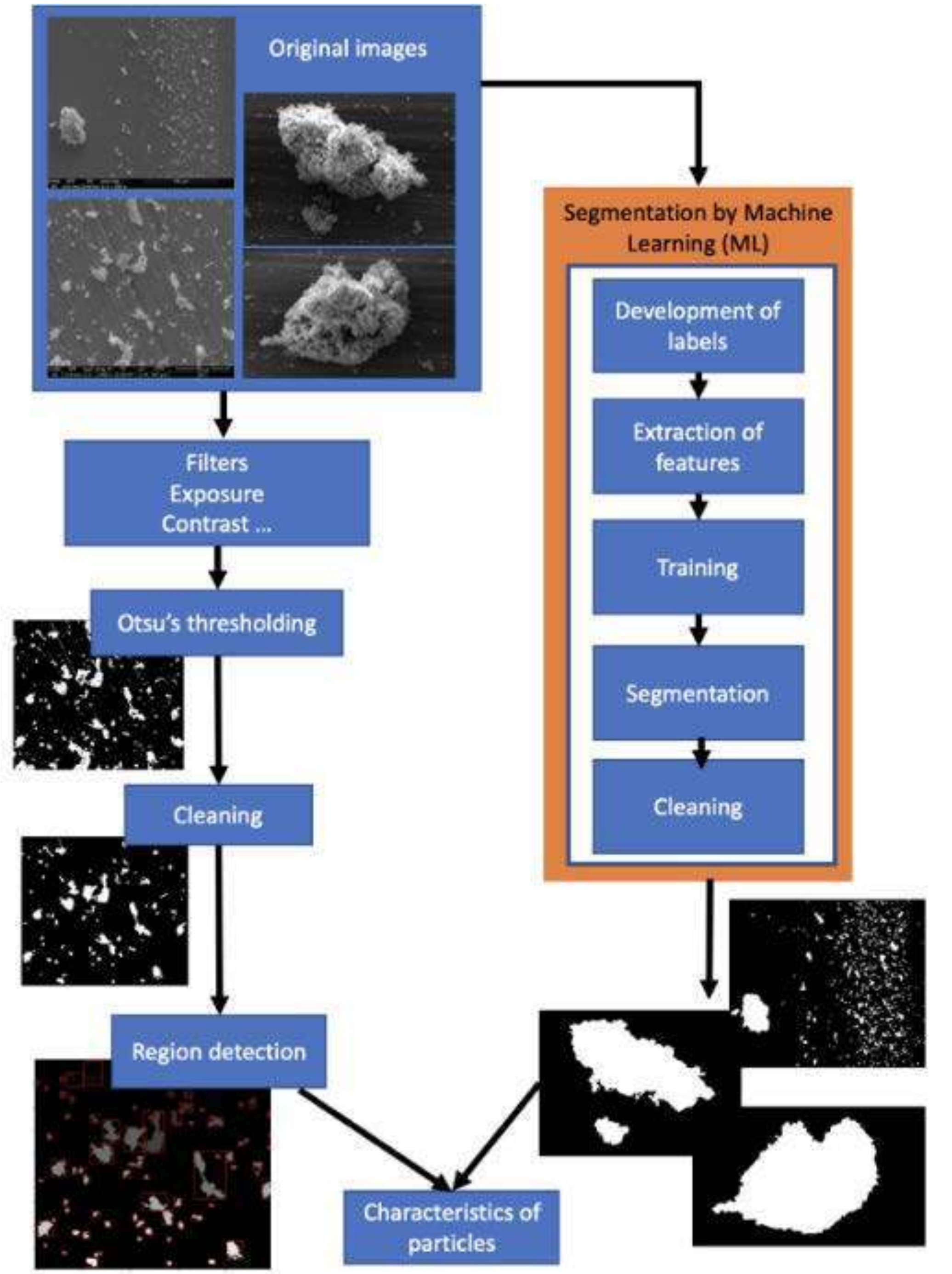

Figure 4: Image Processing steps. Initially, segmentation by thresholding will be preferred. Thanks to the filtering and cleaning operations the results will be very satisfactory in most cases. For complex texture particles, if the user feels that the result is not satisfactory (as shown in Fig. 5), ML segmentation (orange) is required.[7]

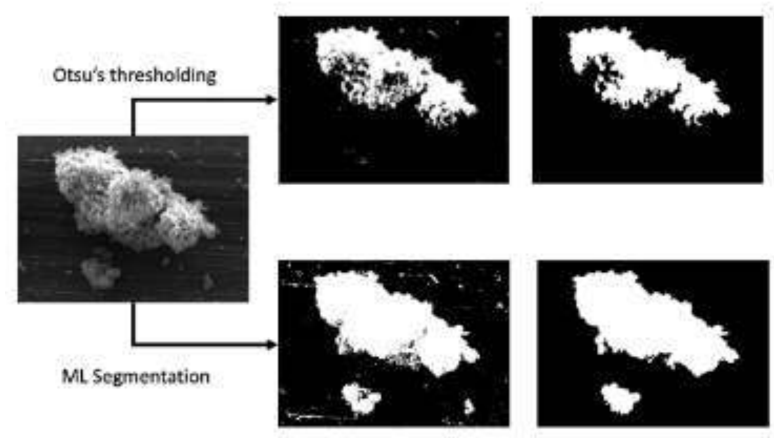

Figure 5: Particle with a texture that does not allow segmentation by Otsu's thresholding. To solve this problem ML segmentation is used.

To overcome this, another code has been developed, it uses machine learning (ML) algorithms and allows better segmentation in the case of complex textures.

Several intelligent algorithms have been trained (neural networks (MLP), random forest (RF),Support vector machine (SVM), votting classifier, bagging MLP, bagging RF and bagging SVM to discern whether a pixel belongs or does not belong to the particle. This commonly used method for the analysis of medical and hyperspectral images has been adapted to third body images.

The first step is the elaboration of labels. Some "representatives" particles of the problem (training particles) are chosen and undergo a manual clipping as precise as possible to give the labels belong or do not belong to the particles.

The training particles will then be analyzed using openings and closing by reconstruction in order to obtain a set of morphological profiles. These profiles are complemented by another set, this time focused on textures. These texture descriptors are established through the use of rotational invariant Local Binary Pattern (LBP) [12], three radius are considered.

Thus each pixel of the training image has 9 features (6 from morphological profiles + 3 values of textures) used for training and validation of machine learning models.

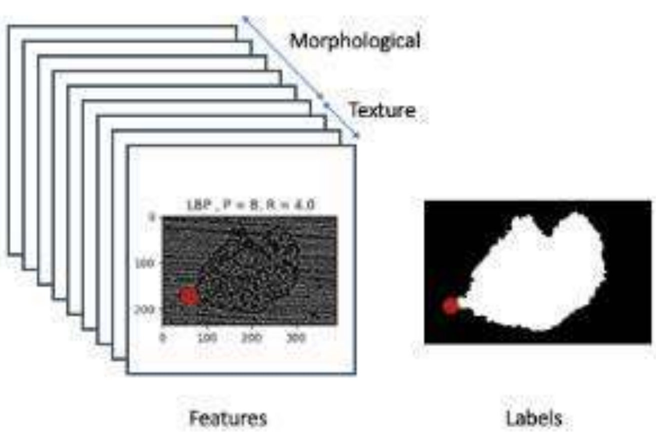

Figure 6: Illustration of composition of training data base.

Follows the training phase, it was chosen to use the same number of black and white pixels to constitute the training and validation base. This balanced database is divided in three parts with the training , validation and test sets corresponding respectively to 70%, 20% and 10%.

Thanks to the validation set, it is possible to realize a performance evaluation to choose the most efficient parameters for features with respect to the morphological and texture profile as well as the radius for LBP.

Following the study of the performance of the different models through evaluation coefficients such as specificity, sensitivity and DICE, only two models are retained, MLP and MLP bagging.

It is therefore possible to segment complete images containing several particles with a texture similar to the training particle.

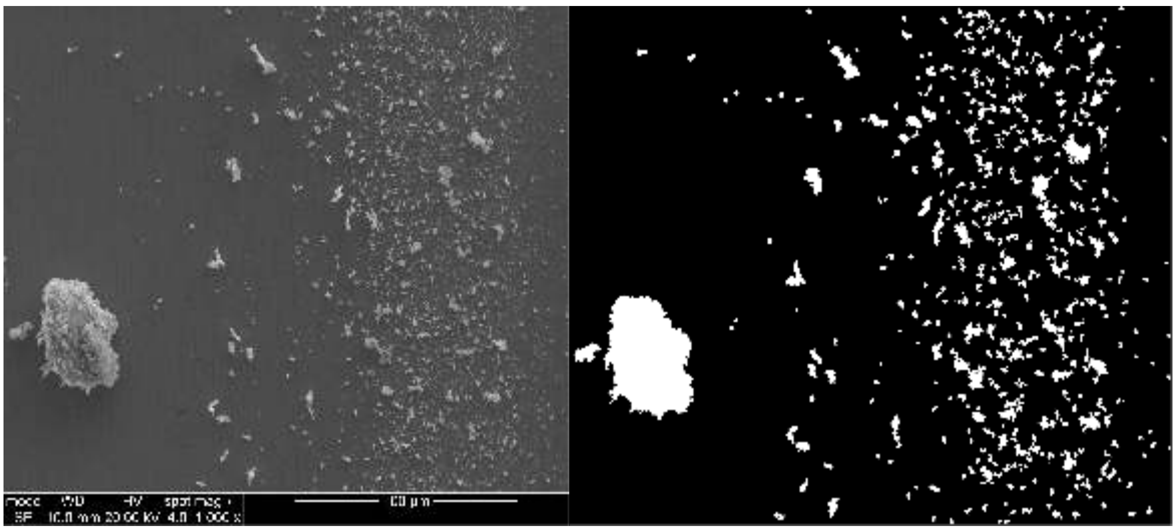

Figure 7: Machine learning segmentation generalization. LEFT : Original image, RIGHT : segmented image

From this binary image it is now possible to extract the properties of the segmented regions. To date, the criteria for describing third body particles are circularity, regularity, elongation, perimeter, area and roundness.

The list of these recurring criteria in tribology is eventually to be increased in order to carry out a correlative study that will allow to link the experimental data (coefficient of friction, sound, acceleration, etc.) with the third body particles characteristics, using machine learning, This will complement and enrich the work of Jaza[13,14].

4. CONCLUSION AND OUTLOOKS

During this study a protocol was presented allowing the segmentation of third body particles according to the complexity of their texture.

First thanks to segmentation by thresholding for smooth textures, then thanks to the use of machine learning for powdery textures.

It is possible to train and save several neural networks depending on the experimental conditions and the type of textures obtained, for example a network per production atmosphere. Thus all the particles produced under a given atmosphere can be segmented thanks to the same trained networks.

For use in tribology segmentation is only a step to obtain the characteristics of the third body.

That is why it is interesting in the future to automate the process. For this the next studies will be oriented towards the use of deep learning and more specifically towards networks of type U-net, widely proven in medical imaging [15].

However, the final objective is to link the characteristics (morphological, geometric and topological) of the third body to the experimental tribological data. It is possible to approach the problem with the same two approaches as for segmentation, a supervised approach and a non-supervised (machine learning and deep learning) but as there is a desire to understand what are the discriminant and significant parameters, the way of machine learning remains to this day to privilege.

Finally, in a second step, the third body trapped in the center of the track, corresponding to the recirculation flow, will be studied in terms of texture using descriptors from tools such as the cooccurence matrix and will be the subject of further study in order to supplement the extracted knowledge of characteristic correlation of wear particles - tribological data.

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