Analysis of worn surface images using gradient-based descriptors

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***Abstract*—Failures of mechanical systems are strongly related with wear of interacting surfaces in machine elements. Hence, wear monitoring is fundamental to avoid energy and time losses, as well as to prevent definite failures on machines. Wear monitoring can be achieved by capturing worn surfaces images, in which mass losses are represented as non-uniform texture patterns. This work introduces a computational framework to characterize and predict mild or severe wear regimes by using gradient-based descriptors. The HoG and Daisy descriptors were used to codify wear morphologies of worn surfaces images. Once images were coded as gradient patterns, the corresponding descriptors were mapped to a previously trained Support Vector Machine (SVM), allowing to automatically associate a wear regime label. A set of Scanning Electron Microscopy (SEM) images of abrasion worn surfaces were used to validate this work. The proposed framework achieves accuracy results of 94% and 96% using the Hog and Daisy descriptors, respectively.**

Wear monitoring, Abrasive wear regimes, HoG descriptor, Daisy descriptor.

I. INTRODUCTION

One of the greatest causes of unavailability of machine components is wear. Wear results from surfaces interaction which promotes mass losses as much as energy and time losses. All these losses have associated high economical costs due to the corresponding maintenance and reparation events [1]. To improve the availability of machines an optimized reliability must be guaranteed in order to decrease unexpected shut-down of machine elements [2]. The wear monitoring is an adequate way to prevent failures of mechanical systems.

Wear monitoring can be executed by acquiring images from worn surfaces and obtaining wear indexes using image processing techniques. Imaging methods have been well studied in last years since it has several advantages with respect to other semi-online and offline approaches such as mass or volume losses measurements, ferrography, topographical difference, among others [3]. The vision-based wear monitoring also allows obtaining a low cost, automated, accurate, online and non-contact inspection of worn elements [3].

A particular application of image analysis for monitoring the wear progress is to identify the wear regime exhibited by a component surface during its operation. Usually, sliding and abrasive wear of ferrous alloys produce two main wear regimes, mild and severe [4], [5]. Severe wear must be strongly inhibited during the performance of machine components. As a result, a monitoring system based on image processing techniques will be useful to better prevent catastrophic failures of mechanical systems. Also, it would be expected that a proper image characterization lead to machine learning frameworks with the ability to perform prediction of wear regimes.

Different approaches have been used to characterize the wear behavior of materials using image-based techniques. Some applications include the cutting tool wear detection [6], [7], the wear debris [8], [9] and the laboratory wear tests characterization [3], [10]–[13]. On the other hand, the progress of wear processes can be represented through the analysis of worn surfaces images [6], [13]. In particular, one of these investigations analyzed SEM images of worn surfaces [14], finding a quantitative correlation between morphological features and the wear intensity [3], [10], [12], [13], [15].

One of the most common image processing techniques is the edge detection or operators estimation [9], [10], [13]. These techniques are suitable to detect edges in an image by means of the computation of operators such as gradient and direction [16] or texture-based operators [7]. The wear intensity of a determined worn surface can be predicted according with the quantity of edges recognized [10], [17]. Notwithstanding the above, some errors could be produced as a result of the recovered isolated noise gradients during the operators estimation. Recently, in [18] was proposed a computational strategy to classify mild and severe regimes by using a histogram of oriented gradients (HoG) to represent the surface features. This approach achieved an interesting performance but lost the analysis of other gradient based descriptors, as well as the exploration of non-linear kernels on learning strategies.

In this work a computational framework that evaluate the HoG and Daisy descriptors over worn surface images is introduced to predict mild and severe regimes. These descriptors code histogram of gradients using different geometrical architectures over the complete image, which result in different properties of description. Once the images are coded, a Support Vector Machine (SVM) model allows to automatically predict the wear regimes present at surfaces. To get a better learning classification, a radial basis function was herein implemented, which admits non-linear performances on

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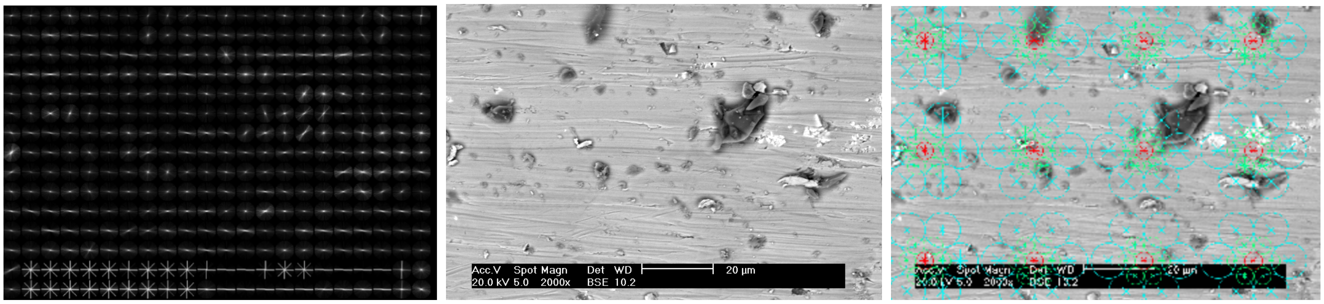

Fig. 1: Example of the coding structures for both gradient descriptors herein evaluated. In the left image the typical performance of HoG descriptor is illustrated, that regionally coded gradients on orientation histograms. In the middle image is the original image that corresponds to a severe class. In the right is displayed image the geometry of kernel used to compute gradients in Daisy descriptor.

feature space.

II. METHODS

A. Dataset Description

Scanning Electron Microscopy (SEM) images of worn surfaces were selected to make the analysis in the present work. Worn surfaces were resultant of the abrasion wear tests carried out in laboratory, where different cast irons were put in sliding contact against different kind of abrasives. Additional details of the wear test conditions can be found elsewhere [18], [19]. The SEM images allow to identify surface patterns related with the kind of mechanical or chemical effects generated during the wear process. Therefore, the worn surfaces analysis is used to correlate the surface features with the wear behavior. The behavior of each combination of an iron cast with a particular abrasive resulted in a particular wear rate. High and low wear rates are associated with severe and mild wear regimes, respectively. For whole validation was used a dataset with a total of 50 samples, distributed in 29 samples labelled as severe, while the rest 21 images were labelled as mild.

An array of 256x256 pixels characterized the SEM images, representing 3D surface texture. Worn surfaces with mild wear regime had a smooth appearance and low amount of shallow scratches, meanwhile worn surfaces with severe wear regime had a rougher surface with plastic deformation traces and deeper scratches [19]. In this way, surface features, captured on images, could be modelled as non-uniform gradient patterns. On one hand, severe wear generate strong texture patterns. On the other hand, mild wear produces a smooth and an uniform gradient. Nevertheless, an automatic computational prediction of wear severity is a challenge task because the huge variety of gradient patterns along the surface. In this work, a local gradient quantification is carried out by using two well know gradient codifications: the HoG [20] and Daisy [21] descriptors. The resulting descriptors over a worn surface image are shown in Figure 4. A complete description of these type of descriptors are presented in next subsections.

1) HoG representation: HoG descriptor is a well know gradient-based representation that result useful to code mild and severe wear surfaces captured on images. The HoG descriptor achieves a dense and redundant estimation of gradient histograms, which are computed following a sliding window. To remove point gradient artifacts, the histograms are normalized with respect to a neighborhood. The histogram of gradients gives an idea of main orientations reported into a specific region, while the dense computation along the image emerge to be robust with respect to the variability of representation of surface features of wear regimes.

The dense HoG computation starts by splitting the image sample into a set of regular patches $\mathbf{c_i}$. The gradients $\bigtriangledown \mathbf{c_i}$ into each patch are summarized using a histogram of gradients $\mathbf{H_i}$. In this case, bins ω are defined by intervals of orientations, which are weighed w.r.t the norm of each gradient vector, as: $H_i(\omega) = \sum_{\{\phi(\bigtriangledown \mathbf{c})=\omega\}} \|\bigtriangledown \mathbf{c}\|$. Each of the bins ω are normalized regarding the sum of the total of norm gradients. Additionally, the HoG descriptor has a block normalization with respect to the total number of bins of whole histograms in a specific region, as shown in: $\mathbf{b_n} = \frac{\mathbf{b_n}}{\sqrt{\|\mathbf{b_n}\| + \varepsilon}}$. It is expected that worn surfaces with mild wear will be represented with uniform histogram with equal probability for all gradient orientations. In contrast, in worn surface images with severe wear some patches are represented by asymmetric histograms describing non-uniformity of the surface.

2) Daisy representation: An additional gradient-based representation of worm surfaces was herein achieved with Daisy descriptor [21]. This multi-scale gradient descriptor was originally developed for dense wide-baseline matching. However, because the robustness, invariance to scale and rotation, as well as for fast computation, nowadays is widely used in task of recognition, of objects of interest. In this approach is SEM image I is convolved several times with a Gaussian kernel G_Σ, capturing different gradient orientation maps $o(x, y)$. This process can be expressed as: $\mathbf{G_o^\Sigma} = \mathbf{G_\Sigma} * \frac{\partial \mathbf{I}}{\partial \mathbf{o(x,y)}}$. A total of eight convolved orientation maps are obtained, which operates at different Gaussian scales.

Hence, at each pixel location is fixed a set of concentric circles as illustrated in Figure 1 to compute different orientation histogram, that represent each of the subregions. This particular structure of concentric circles allows to be

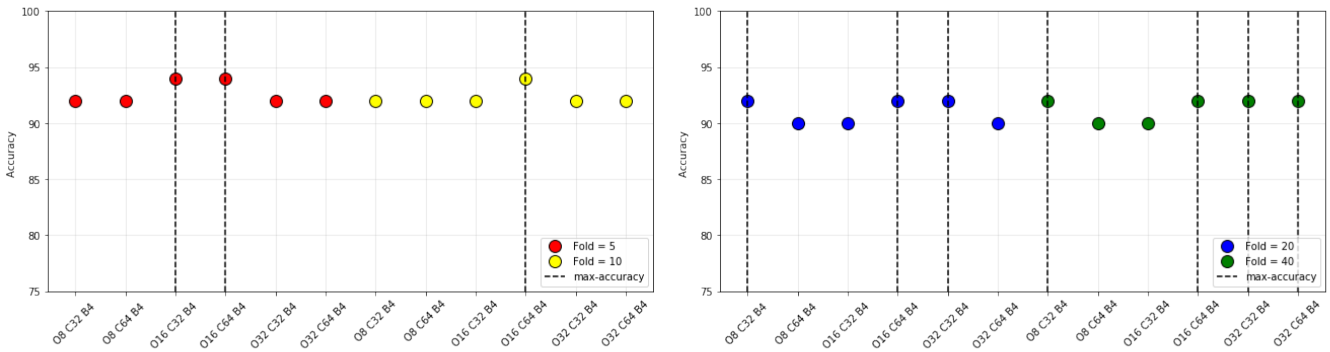

Fig. 2: Results of the accuracy as a function of the parameters of the HoG descriptor and k-fold.

invariant to rotation, allowing, for instance, characterize same severe regime patterns that are rotated at different SEM image samples. Also, the multi-scale nature allows to better differentiate among mild and severe regimes, being present the gradient patterns in all scales for severe regimes. An additional advantage of circular configuration is the design of symmetrical kernels that could be computed faster than other descriptors, allowing online wear monitoring.

B. Support vector Machine

The recognition of each worn surface is carried out by a SVM classifier given their robustness, generalization aptness, accuracy and low computational cost [22]. The present approach was implemented using a Radial Basis Function (RBF) kernel. This kernel function expressed as $K(x_i, x_j) = exp(-\gamma x_i - x_j{}^2)$, with (x_i, x_j) difference among samples of mild and severe wear regimes. This samples are characterized by a $n-$dimensional vector with coding of the HoG or Daisy gradient descriptors, *i.e.,* $x \in R^n$. From such features into the descriptor are built optimal hyperplanes to separate them by a classical max-margin formulation. A (γ, C)-parameter sensitivity analysis was performed with a grid-search using a cross-validation scheme and selecting the parameters with the largest number of true positives.

Evaluation in this work was carried out to analyze the performance of gradients-based descriptors: HoG and Daisy. Different configuration on descriptors were analyzed under a k-fold validation scheme. Specifically, the statistical validation was carried out using different set of folds, defined as: $k = [2, 10, 20, 40]$, allowing to cover the range for several SVM learning models built from different proportion of images in training. Also, results are reported in terms of accuracy, that counts the proportion of true positive detection over whole test set.

III. RESULTS

The first evaluation was carried out using a HoG descriptor changing the main parameters of the descriptor, *i.e.*, number of orientations (o), size of the patch in the images (c) and number of blocks (b) used to normalize the histograms. In Figure 2 a summary of the obtained results for different HoG configurations (o, c, b) and under the different fold schemes is illustrated. A maximum average accuracy of 94% was achieved using the configuration of $o16, c32, b4$ and with a $K = 5$ folds. In other words, a high accuracy is already achieved with low k-folds, which means that much computational cost can be saved. The same result was also found before, where in addition a lower dispersion of data and similar maximum values of accuracy were acquired at low k-folds [18]. SVM classifier

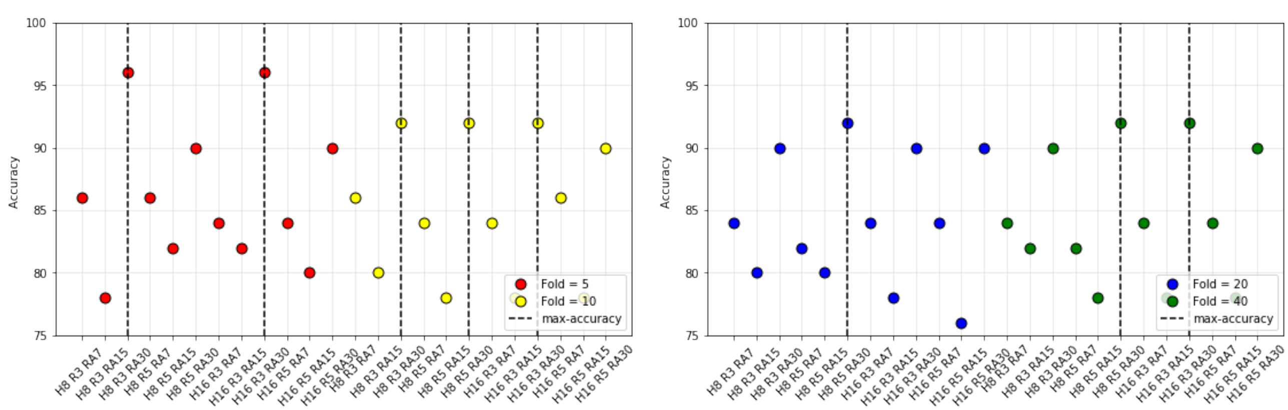

Fig. 3: Performance of the model in function of the parameters of the Daisy descriptor and Fold.

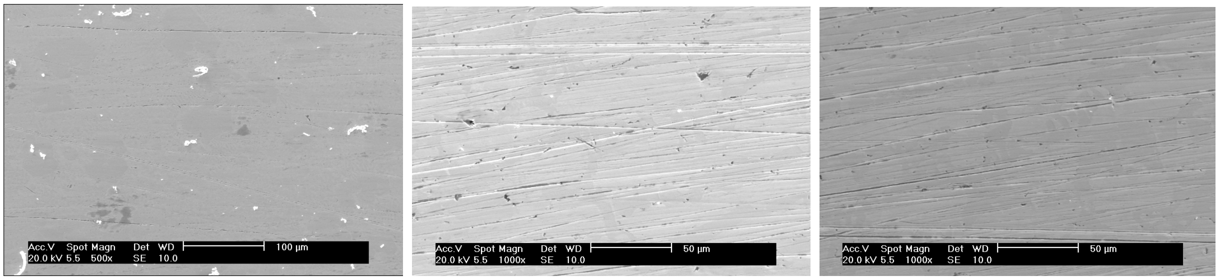

Fig. 4: Examples of misclassified images by the SVM model using the descriptor HoG and Daisy.

resulted in more stable behavior of accuracy in comparison with the behavior observed previously with Decision Tree and the Gaussian Naive Bayes classification models [18]. Then, SVM has a similar stability in accuracy to the behavior of the Random Decision Forest model.

In general, the best results are obtained with 16 orientations in histograms and using a block normalization of 4. Such configuration is sufficient to characterize much of the surfaces that allows to properly predict wear regime classes. Similar results were obtained with the HoG computation and applying other classifier models [18], where 16 orientations in histograms yield in the highest accuracies. On the other hand, patches of 64 are sufficient to capture gradient patterns that represent worn surface signatures. Because the strong changes of gradients that represent wear severity, histograms with relative few bins are sufficient to represent non-uniform distributions. Basically, this descriptor is relative stable with almost all configurations, standing out the geometrical features that characterize the surfaces.

A second evaluation was performed from Daisy descriptor. For doing so, the images were codified with different variation of the number of histograms calculated per ring (h), number of rings used in the descriptor (r) and radio in pixels of outer rings (ra). In Figure 1 the results achieved by Daisy descriptor using different configurations are shown. In this case, a maximum average accuracy of 96% was found at $k = 5$ folds again, as observed for HoG descriptor.

The best results of accuracy were obtained by keeping the radio in pixels of outer rings (ra) in 30. No effect was observed for the other configurations parameters. Results of the Daisy descriptor show that values of accuracy were unstable and sometimes leading to low values between 75% and 80%.

As noted in the above results, accuracies of almost 95% were achieved with both HoG and Daisy descriptors. As a consequence, there are some worn surfaces images being misclassified. In other words, some images are being classified as mild when they are really severe, and vice versa. Then, an analysis was made to found those images and which were the same for both HoG and Daisy descriptors. In Figure 4 misclassified images using both gradient descriptors are displayed. These images correspond to mild worn surfaces but the SVM automatically classified them as severe. To understand this behavior, appearance of these images must be discussed. Firstly, in the left image it can be observed some white particles that maybe do not represent the wear marks present at the surface, which has a low quantity of scratches produced by abrasives. these particles could be contamination products since surface did not evidence severe wear. On the contrary, the middle and right images surface features are characterize by many scratches which justified that results, *i.e.*, they represent a severe wear regime. However, their wear rate was not so high as for those severe labelled conditions and probably were at the transition region between mild and severe wear regimes. This result suggest that maybe a third label must be created and analyzed in future works, which correspond to those conditions not being mild nor severe classes, but being between them.

IV. CONCLUSIONS

This work presented a computational classification framework that is able to predict mild and severe wear regimes from worn surface images. The worn surfaces were fully characterized using the dense histogram of gradients (HoG) and the efficient dense Daisy descriptor. The proposed approach achieved a quite perfect classification, because the proper representation of non-uniform texture patterns of corresponding wear regimes.

The accuracy results obtained with the HoG descriptor were mostly stable for the configurations evaluated and achieving a maximum accuracy of 95%. The stability of accuracy values with the HoG descriptor could be attributed to the SVM model, as obtained previously with others models such as Random Decision Forest. Meanwhile, the Daisy descriptor computations exhibited more unstable values of accuracy for the parameters used in its configuration and 96% of maximum accuracy. For both cases, maximum values of accuracy were produced at low values of k folds.

Future works include a local analysis of worn surfaces that allows a better understanding of the phenomenon, an inclusion of a new wear class corresponding to those wear conditions between mild an severe, and the evaluation with sequence of images that allows an online application.

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