Tool wear monitoring in milling using aZIBO shape descriptor

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Abstract

In this paper, a tool wear monitoring process is carried out in order to determine the insert wear condition and to ensure the optimal usage of tools before their replacement during metal machining operations. The dataset is composed of 53 cutting inserts. All of them were pre-processed and their edge wear was segmented resulting in 212 edges set. To describe the wear shape, aZIBO shape descriptor was used and its results were compared with two classical descriptors, Hu and Flusser. The classification was carried out using kNN with 1, 3, 5, 7, 9 and 11 neighbours and six distances: Cosine, Euclidean, IntersetcDist, ChiSquare, SqDist and Cityblock. Two classifications have been carried out: One of them using three different classes (Low, Medium and High wexar -L, M and H, respectively-) and the other one with only two classes: Low (L) and High (H). aZIBO descriptor offers better results than the classical ones obtaining hit rates of 60.84% and and 81.13% using the L-M-H and the L-H labellings, respectively.

Keywords: aZIBO, Hu, Flusser, Tool wear, kNN

1 INTRODUCTION

Tool replacement operations lead to significant costs in metal machining processes. Not only the cost of cutting tools is important, but also, and maybe much more important, indirect costs derived from the unproductive time needed to perform the tool replacement. Usually, the replacement process consists of early stopping rules that reject the inserts irrespective of their actual wear condition. This kind of decisions make inefficient the machining operations in a very competitive production system. Tool wear condition can be determined manually or by automatic monitoring processes. Obviously automatic processes are preferred in highly automated systems. Automatic tool wear monitoring is traditionally based on indirect variables related to the production process like cutting time or number of parts produced, but these variables do not ensure the optimal usage of tools nor lead to minimal replacement costs, resulting in important economic losses. For these reasons, optimized monitoring systems based on tool wear measurement must be developed to increase competitiveness.

The main tool wear monitoring methods are detailed in [5, 13]. Nowadays, there are two main approaches to measure tool wear: direct and indirect measurement methods. Indirect methods provide wear estimates by monitoring observable variables related to wear, such as cutting forces [21, 20], vibrations [18] or power [19, 1]. Although these methods are the most used, noise signals at industrial environments severely undermine the quality of these estimates [14]. On the other hand, direct methods, usually based on computer vision systems, are definitely better in terms of accuracy and reliability. So the aim of this paper is to efficiently estimate insert wear to enlarge tool life and to decide about the right time for tool replacement using shape descriptors.

In the recent years, many shape descriptors have been proposed for multiple purposes. For example, in [8] two descriptors are proposed, multiscale fractal dimension and contour saliences using a graph based approach called image foresting transform. This method returns a root map, a cost map and a label map containing the relevant information of the contour points and its relationship with its influence area points using contour and skeleton based techniques. Later, this method was improved exploiting the resemblance between content-based image retrieval and image analysis in order to develop two new descriptors: contour and segment saliences testing their retrieval system with a fish dataset [7].

The concept of tensor scale, which is a morphometric parameter that unifies the representation of local structure thickness, orientation and anisotropy, is exploited by Andaló et al. [2]. The authors proposed a shape salience detector and descriptor which, as the previous method, use the Image Foresting Transform. Another method which uses information of the boundary points is the one proposed by García-Ordás et al. [16]. In

this work the minimum circumscribed circumference to the shape is constructed. Then, this region is divided into several bins and finally the descriptor is built taking into account the number of points corresponding to each bin.

Zhiyang Li et al. [15] proposed a geometry-based shape descriptor called ROMS which is a multiscale descriptor defined by the ratio of a triangle middle and side lines in each scale. In the work developed by Zagoris et al. [22] an MPEG-like descriptor that contains conventional contour and region shape features is proposed.

All these methods can be used in multiple applications. For example, in the medical field Hao et al. [11] proposed a method to automatically classify the invertebral disks as healthy or degenerated. The authors used active learning to avoid manual labeling for all training data. Proen et al. [17] focused on iris recognition technologies used in the biometric field. All these approaches can be used for tool wear description.

Besides, nowadays numerous researches are trying to improve efficiency of characterization by combining two or more shape descriptors. One example is the proposal developed by Singh et. al. [6] which is an effective descriptor based on angular radial transform (ART) and polar Hough transform (PHT). ART is used as a region based shape descriptor which represents global aspects of the image and PHT is used as local shape descriptor for detecting linear edges in the insert image. A similar approach is used in [3] based on an innovative trademark retrieval technique with improved performance due to integration of global and local descriptors. Zernike moments coefficients are used as global descriptor and the edge gradient coocurrence matrix derived from the contour information as local descriptor.

In this paper, we use aZIBO descriptor (absolute Zernike moment with Invariant Boundary Orientation) [10] and classical Hu and Flusser shape descriptors to describe the tool wear. The rest of the paper is organized as follows. In section 2, the relevant shape descriptors are described. In section 3, the process for obtaining the dataset, the experiments and results are shown. Finally, in section 4 conclusions are discussed.

2 METHODS

2.1 Classical descriptors. Hu and Flusser

Two classical descriptors, Hu and Flusser, were used to classify inserts wear. The results were compared with a new descriptor called aZIBO. Hu descriptor extracts seven normalized moments

yielding a descriptor which results invariant to rotation, translation and scale [12]. Flusser descriptors are six invariant affine moments [9].

2.2 aZIBO

aZIBO is a shape descriptor proposed in [10] which combines global and local descriptors. In summary, the process is the following. Firstly, aZIBO uses Zernike moments as global shape descriptor employing the module of the first 36 coefficients up to the 10th order. Zernike moments module is invariant to rotation, which makes the global descriptor robust no matter what the image orientation is.

EGCM (Edge Gradient Coocurrence Matrix) is used as local descriptor. The first step to construct EGCM is to obtain the boundary points of the image uniformly sampled. In this case, the method proposed in [4] was used. An example of this detection process is shown in Figure 1.
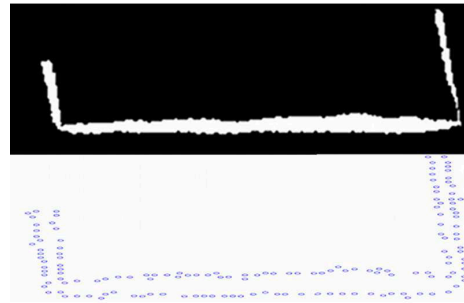

Figure 1: Example of boundary points extraction. Upper side: original image. Lower side: boundary points extraction.

The gradient orientation is calculated for each boundary point following the equation (1).

$$\phi(x,y) = \arctan\left(\frac{I(x+1,y) - I(x-1,y)}{I(x,y+1) - I(x,y-1)}\right) \quad (1)$$

All these gradient orientations are quantized to the following eight: East, North-East, North, North-West, West, South-West, South, South-East.

The next step is to construct the EGCM (Edge Gradient Coocurrence Matrix). We take into account the 8 neighbors of each boundary point pixel, considering only those which are part of the contour. The process is shown in Figure 2

To improve the description method, the local descriptor is made partially invariant to rotation. First of all, the dominant orientation ϕ_d of the image is obtained. Let $p_1 = (x_1, y_1)$ and $p_2 = (x_2, y_2)$ be the most distant points on the contour.
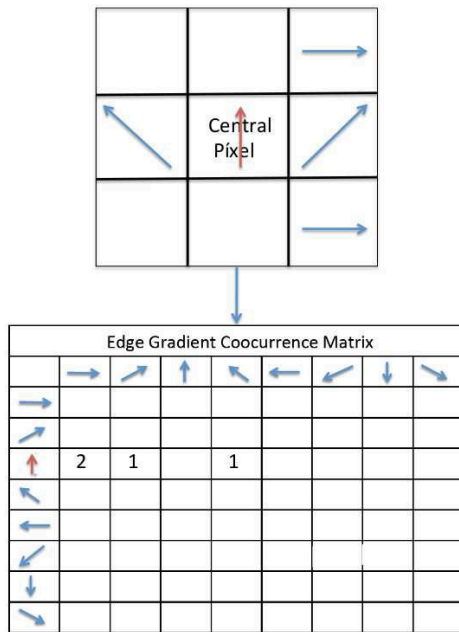
Figure 2: Edge Gradient Coocurrence Matrix construction for one pixel.

ϕ_d is considered as orientation of the vector $\overrightarrow{p_1 p_2}$:

$$\phi_d = \arctan\left(\frac{y_2 - y_1}{x_2 - x_1}\right) \qquad (2)$$

So the eight orientations in the EGCM are shifted placing the dominant orientation in the first position in the matrix. If EGCM is $[\phi_1, \phi_2, ..., \phi_d, ..., \phi_8]$, then IEGCM is $[\phi_d, ..., \phi_8, \phi_1, ..., \phi_{d-1}]$. Therefore, the same description is obtained for one image wherever its orientation is. Once this partially invariant matrix is constructed, the local descriptor is obtained by concatenating the eight matrix rows to obtain a 64-element descriptor. This process is not important in our case because all images have been pre-processed so that all of them have the same orientation as explained in section 3.1.

Therefore, the final descriptor is composed of the module of the first 36 Zernike moments extracted from the original binary images and the Invariant Edge Gradient Co-occurrence Matrix concatenated by rows.

3   EXPERIMENTS AND RESULTS

3.1   Dataset

The aim of this paper is to efficiently estimate cutting inserts wear and to improve the decision making for tool replacement time using shape descriptors. To deal with this, a set of 53 inserts with different levels of wear were selected. Figure 3 shows some images as example.
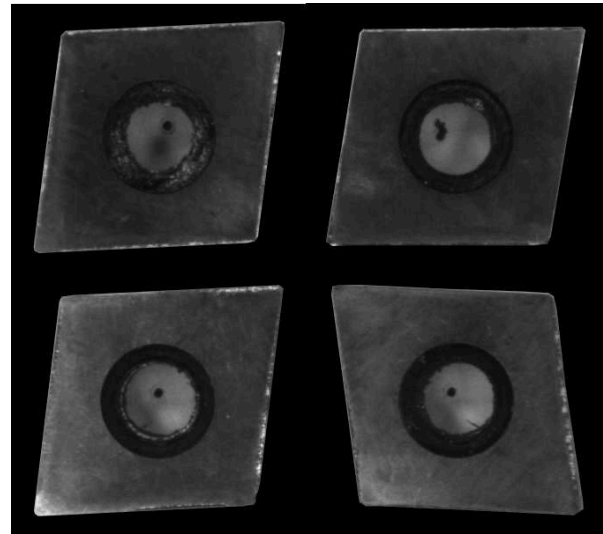

Figure 3: Inserts dataset example. The insert in the south-east presents a wear of medium level in the right border, a low level wear in the left and it has not wear in the other two edges.

The insert gray-scale images with masked background are subjected to a pre-processing step that yields four new images, one for each cutting edge in horizontal position. The pre-processing is carried out as follows.

The first step consists on removing the central portion of the insert, masking out a circular region. Firstly, we need to determine the center and radius of the circle. To determine the circle center, the image is binarized using a 0.01 threshold - obtained empirically -, resulting in an image with the pixels of the insert area set to 1 and the rest to 0. Then, we calculate the centroid of this area that will be the center of the central circle. Using this binary image, we also obtain the length of the major axis, being the radius of the circle 1/5 of its length. After this process, we obtain a gray-scale image with both its background and central region masked out. This image will be used to extract the four cutting edges.

The next step is to describe the edges extraction process. Only the extraction of the west edge is explained; the rest of edges -north, east and south- are extracted applying the same procedure rotating the original image 90°, 180° and 270°, respectively. Using the gray-scale image resulting from the previous step, a vertical Sobel filter is applied to detect the inserts contours. These contours are then dilated and opened, and vertically projected onto the horizontal axis. The first element in this projection non-equal to zero indicates the

x coordinate of the image where the cutting edge starts. Once the starting x coordinate is determined, the image of the cutting edge is cropped from the starting x position to a 100 pixels width while maintaining the same height as the original image. A parametric margin is added that allows us to increase the crop area, because experimental tests showed that some inserts lost some edge pixels due to too tight crops.

Once the four cutting edges have been extracted and their crops have been rotated to horizontal position (leaving the edge heading to south), the edges are aligned to horizontal position. Since inserts are not square-shaped but rhomboid-shaped instead, and their cutting edges are not aligned with the vertical and horizontal axis, the edges images need to be rotated to obtain alignment of the edges with the horizontal axis. To carry out this operation, a horizontal Sobel filter followed by a dilation is applied. The resulting image is filtered to remove smaller objects leaving a binary image containing just the cutting edge. This edge is inscribed in an ellipse whose major axis is obtained. The orientation of this major axis is the same than the orientation of the cutting edge with respect to the horizontal axis. After obtaining this orientation, the original cutting edge image is rotated to compensate this orientation, leaving the cutting edges aligned to horizontal position.

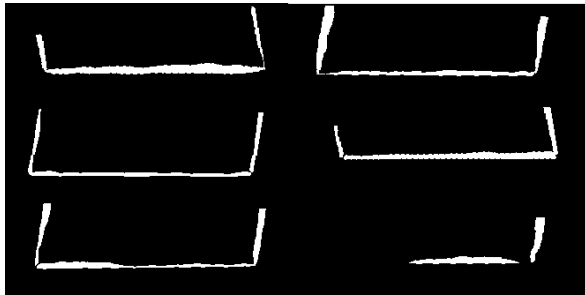After all this process, a dataset composed by 212 binary images is obtained. Figure 4 shows an example.

Figure 4: Dataset example.

3.2 Setup

Many retrieval methods exist but most of them are very expensive in terms of computational cost. kNN classification was used with k equals to 1, 3, 5, 7, 9 and 11 and six distances: Cosine, Euclidean, Intersect, Chisquare, SqDist and Cityblock to classify the concatenation of the global and local shape descriptor explained in the previous sections. Two types of classification were applied: the first one considering three classes (low

(L), medium (M) and high (H) wear) and the second one considering two classes (low (L) and high (H) wear).

3.3 Results

As aforementioned the classification was carried out using six distances. In Tables 1 and 2 the best hit rates obtained in the classifications using the three description methods (aZIBO, Hu and Flusser) are shown. Cosine, ChiSquare, SqDist and Cityblock represent always the best cases. As shown, aZIBO obtains better results than classical descriptors obtaining a hit rate up to 60.37% when using three wear classes and 81.13% when using two wear classes.

Table 1: Inserts classification using aZIBO proposal and Hu and Flusser classical descriptors with k equals to nine and Cosine, ChiSquare, SqDist and Cityblock distances using 3 classes labeling.

	Cosine	ChiSquare	SqDist	Cityblock
aZIBO	58.96%	57.07%	60.37%	59.43%
Hu	55.66%	56.13%	59.91%	58.49%
Flusser	57.07%	58.96%	57.08%	57.08%

Table 2: Inserts classification using aZIBO proposal and classical Hu and Flusser descriptors with k equals to nine and Cosine, ChiSquare, SqDist and Cityblock distances using 2 classes labeling.

	Cosine	ChiSquare	SqDist	Cityblock
aZIBO	81.13%	80.66%	81.13%	81.13%
Hu	76.89%	79.72%	79.25%	80.19%
Flusser	79.25%	78.30%	75.47%	75.47%

Figure 5 shows with more detail all the results for aZIBO, Hu and Flusser, for all k values and the six distances.

As we can see, L-H classification always offers better results than L-M-H classification although it provides less information. Also, aZIBO outperforms classical descriptors in almost all cases.

4 CONCLUSIONS

A tool wear monitoring system has been developed to determine the edge condition of metal cutting inserts. To carry out this process three shape descriptors were evaluated using an edge wear dataset made of 212 images and two different classifications, one with three wear classes
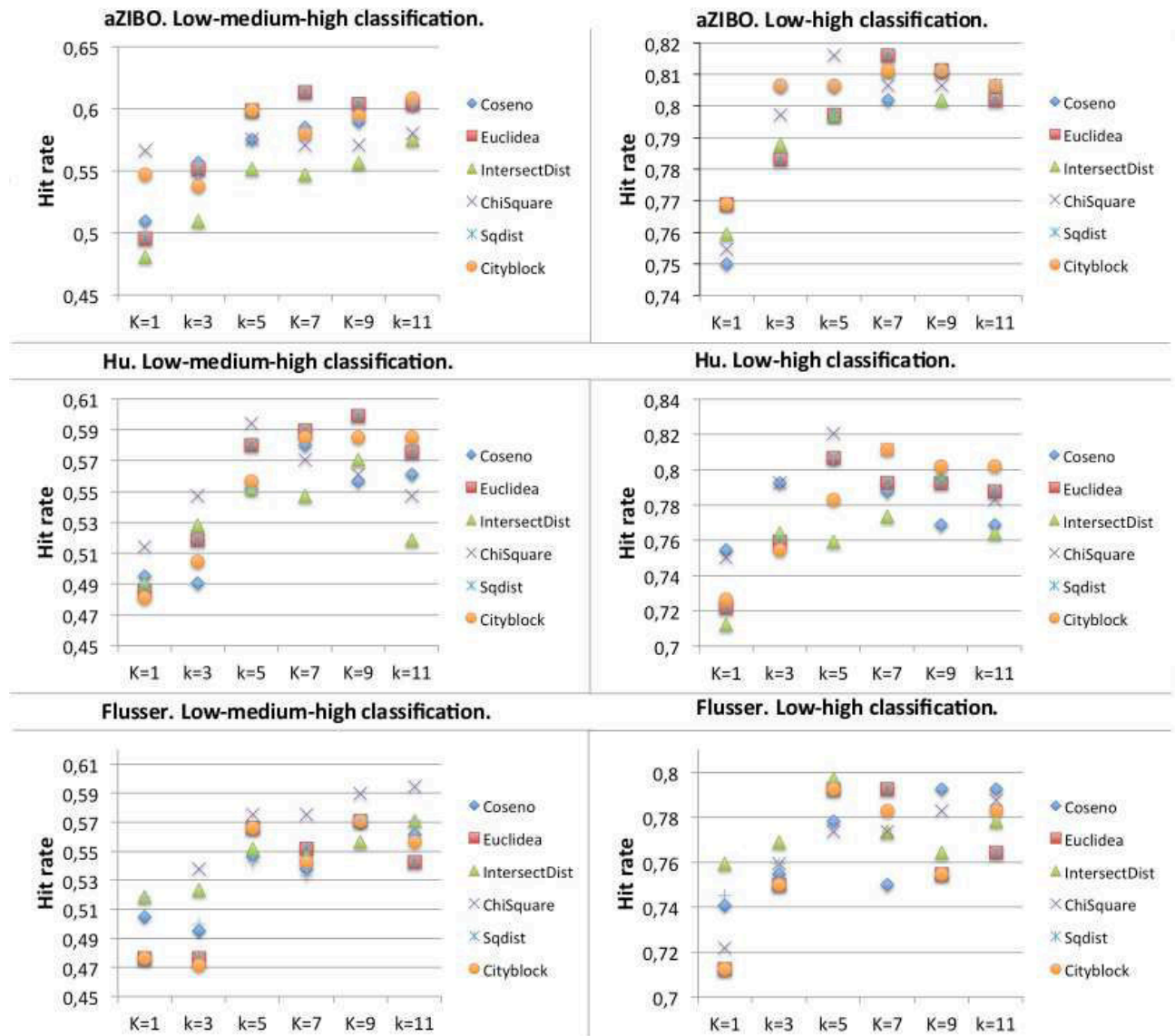
Figure 5: kNN classification for the six distances and different values of k using aZIBO, Hu and Flusser and two kinds of labeling datasets: L-M-H and L-H classes.

(low, medium and high) and the other one with two classes (low and high). Two classical moment descriptors, Hu and Flusser, were firstly tested. The best results for this initial test were 59.91% of hit rate achieved using Hu and Square distance with three classes classification, and 80.19% using Hu and Cityblock with two classes. Secondly, the recently developed aZIBO descriptor based on Zernike and contour points orientations was evaluated. Results in this case indicates 60.37% of hit rate based on three classes and 81.13% of hit rate using the binary classification, that is an outperformance of 0.7% a 1.17% with regard to the moment based descriptors. Furthermore, aZIBO descriptor shows more stability against distance metric used in the k-nearest neighbor process, being the maximum hit rate difference 0,47% instead of 3,3% obtained with Hu and Flusser. Therefore, it can be concluded that the use of aZIBO to determine cutting tool wear increments the performance of monitoring systems and it represents an interesting approach.

Acknowledgements

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