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aZIBO shape descriptor for monitoring tool wear in milling

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Abstract

The aim of this paper is to estimate efficiently insert wear in metal machining and to improve tool replacement operations. Image processing and classification are used to automatize the decision making about the adequate time for tool replacement. Specifically, the shape descriptor aZIBO (absolute Zernike moments with Invariant Boundary Orientation) has been used to characterize insert wear and ensure its optimal usage.

A dataset composed of 577 regions with different levels of wear has been created. Two different classification processes have been carried out: the first one using three different classes (Low, Medium and High wear -L, M and H, respectively-) and the second one with just two classes: Low (L) and High (H). Classification was carried out using on the one hand kNN with five different distances and five values of k and, on the second hand, a Support Vector Machine (SVM).

aZIBO performance has been compared with classical shape descriptors such as Hu and Flusser moments. It outperforms them, obtaining success rates up to 91.33% for the L-H classification and 90.12% for the L-M-H classification.

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1. Introduction

Nowadays, tool replacement operations are really important in terms of cost for the manufacturing industry. Tool wear is the gradual loss of tool material in the work piece. It is caused by many factors acting on the cutting edge of

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the tool, e.g., chemical wear, abrasion, fatigue or a combination of two or more. Monitoring of tool wear is a critical task for the successful replacement. Monitoring can be performed manually or by means of automatic processes.

In the recent years, several methods for tool wear monitoring have been proposed. An example is the work developed by Wang et al. [1] in which a tool wear monitoring system based on relevance vector machine (RVM) classifier is constructed to carry out a multi-category classification of tool wear status during milling process. In a different line, Sun Jie et al. [2] proposed the use of sensor signals and feature analysis to identify a feature set for effective tool condition monitoring. Some other interesting works focused also on automatic monitoring [3,4].

The main problem is that automatic tool wear monitoring is based, in most cases, on measuring direct variables such as cutting time or number of machined parts. However, these variables do not ensure an optimal usage of the tool, so they are not enough adequate for optimizing tool replacement. For this reason, it is proposed in this paper to estimate automatically the insert wear to decide the optimum time for tool replacement by means of computer vision. Specifically we propose the use of shape descriptors instead of using direct variables.

There are three main ways to describe a shape: contour extraction [5-7], image based and skeleton based techniques [8,9]. There are also methods combining them. In [5], shapes are described based on contour points, resulting in a feature vector that is intrinsically invariant to rotation. Torres et al. [8] proposed two descriptors: multi-scale fractal dimension and contour saliencies using a graph based approach called image foresting transform. Later, this method was improved introducing two new descriptors, called contour saliencies and segment saliencies, exploiting the resemblance between content-based image retrieval and image analysis [9].

There are other approaches that combine local and global descriptors such as the one developed by M.T García-Ordás et al. [10]. This descriptor, called aZIBO, combines the advantages of using the module of Zernike moments and the edge features obtained from a partially rotation invariant version of the Edge Gradient Co-occurrence Matrix (EGCM) [11]. It was used to characterize images from Kimia-99, MPEG-7 and MPEG-2 datasets. In this paper, aZIBO is used to monitoring tool wear and to ensure inserts' optimal usage.

The rest of the paper is organized as follows. In section 2, the employed descriptor is briefly described. Thereafter, the dataset creation is explained in section 3. Finally, results and conclusions are presented in sections 4 and 5.

2. aZIBO descriptor

The shape descriptor aZIBO (absolute Zernike moment with Invariant Boundary Orientation) was introduced in [10]. It is a concatenation of a global (Zernike moments module) and a local descriptor (partially invariant EGCM) and, therefore, it combines the advantages of both.

In the next subsections, the description process is explained.

2.1 Global descriptor

Zernike moments, in particular the module of the first 36 coefficients up to the 10th order, have been used as a global shape descriptor. As it is proven in [10], the module of Zernike moments is rotationally invariant, which makes the global descriptor robust no matter what the image orientation is. Zernike is applied using binary images resized to 128 x 128 pixels.

2.2 Local descriptor

EGCM (Edge Gradient Cooccurrence Matrix), proposed in [11], is used in this paper as a local descriptor. However, several changes were made in order to improve the results and make it partially invariant to rotation. The first step is to obtain the boundary points of the image. In this case, we used a Canny edge detector (see Figure 1).

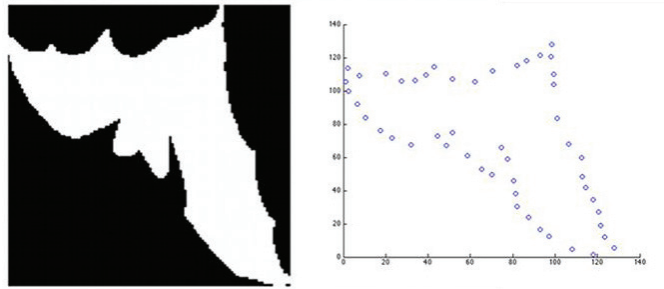


Fig. 1. Original shape (left) and its corresponding boundary points, after the application of the Canny edge detector (right).

Then, the orientation of the image gradient at each point is calculated following the expression (Eq. 1):

$$\phi(x, y) = \tan^{-1} \frac{I(x+1, y) - I(x-1, y)}{I(x, y+1) - I(x, y-1)} \tag{1}$$

These gradient orientations are quantized to: East, Northeast, North, Northwest, West, Southwest, South and Southeast.

Thereafter, the Edge Gradient Co-occurrence Matrix (EGCM) is built taking into account the orientations of the contour points inside a 3x3 neighborhood of each boundary point. See an example in Figures 2 and 3.

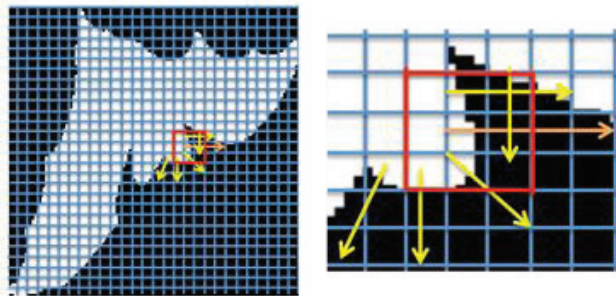


Fig. 2. Gradient orientations of the boundary points in a 3x3 neighborhood centered at the point whose gradient is in orange.

		EGCM							
		→	↗	↑	↖	←	↙	↓	↘
→		1						2	1
↗									
↑									
↖									
←									
↙									
↓									
↘									

Fig. 3. Example of the EGCM of the neighborhood shown in Figure 2.

The EGCM is filled in taking into account the co-occurrences of the orientations of the pixels in the 3x3 neighborhood. This process is carried out for all the boundary points.

In the original work [11], the local descriptor was the concatenation of the EGCM rows. Therefore, it was a vector of 64 elements, which was then normalized to the range [0, 1]. In this case, as well as in [10], the real values were preserved in order to obtain as much information as possible.

Furthermore, this local descriptor is made partially invariant to rotation. Invariance to rotation is an important issue in shape retrieval, as it makes possible to avoid the previous step of rotating all the images of the dataset into a fixed orientation as Anuar et al. [11] did in their work.

First of all, the dominant orientation ϕ_d of the image is calculated (Eq. 2):

$$\phi_d = \arctan \frac{y_2 - y_1}{x_2 - x_1} \tag{2}$$

where (x_1, y_1) and (x_2, y_2) are the coordinates of the most separate points on the contour, p_1 and p_2 . Therefore, ϕ_d is considered the orientation of the $\overrightarrow{p_1 p_2}$ vector.

Thereafter, the eight orientations in the EGCM are shift so that this dominant orientation is placed in the first position in the matrix obtaining partially rotationally invariant EGCM (IEGCM) (Eq. 3):

$$IEGCM = IEGCM(\phi_d, \dots, \phi_8, \phi_1, \dots, \phi_{d-1}) \tag{3}$$

The same description is obtained for one image whatever its orientation is, as it is shown in the example on Figure 4.

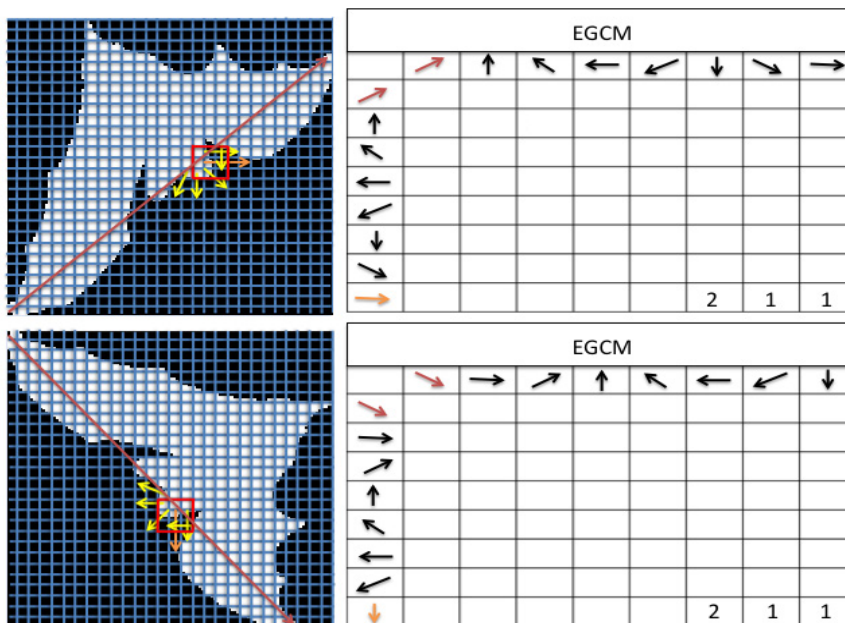


Fig. 4. Invariant Edge Gradient Cooccurrence Matrix construction example.

Finally, the rows of the matrix are concatenated, so the 64-element invariant local descriptor is obtained.

3. Datasets

The original dataset was composed by 53 inserts. An example is shown in Figure 5. The aim of this work is to evaluate the insert wear and, therefore, it is necessary to extract the wear regions from the original images.

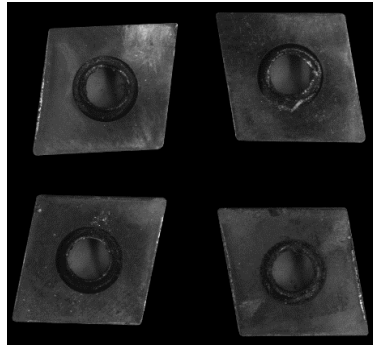


Fig. 5. First inserts dataset example.

In the first step, an edge dataset was created automatically. Each masked (i.e. with background pixels equal to 0) gray-scale images of the inserts are processed yielding four new images, one for each cutting edge in horizontal position.

First of all, the central circle of the insert is removed, so its center and radius has to be determined. Therefore, the image is first binarized using an empirically determined threshold value of 0.01. Afterwards, the centroid of this binary area is considered as the center of the circle, and the radius is $1/5$ of the length of the major diagonal of the insert.

Thereafter the four edges of the tool are extracted. First, a vertical Sobel filter is applied on the grey-level image with the central circle masked out to detect the inserts contours. These contours are dilated, opened and projected onto the horizontal axis. The first non-zero element in this projection indicates the x coordinate of the image where the cutting edge starts. Afterwards, the image of the cutting edge is cropped from the starting position x position with a width of 100 pixels and the same height as the original image had. A parametric margin is added in order to increase the crop area, because experimental tests showed that some inserts lost some edge pixels due to too tight crops. This process is used to extract the left edge of the tool. The process for extracting the others is the same, but previously rotating the original image 90o, 180o and 270o. All these crops are rotated to a horizontal position.

Following, the edges are rotated so that they are parallel to the horizontal axis. To carry out this operation, a horizontal Sobel followed by a morphological dilation is applied. Then, the resulting image is filtered to remove the smallest objects, so a binary image with only the cutting edge is left. This binary image is used to mask the cutting edge in grey level cropped image. Finally, the orientation of the major axis of the ellipse containing this edge is estimated, so the edge is rotated to compensate this orientation and leave it in horizontal position.

In the end, a dataset composed by 212 images is obtained, i.e., 4 edges for each of the 53 inserts. An example with some images of this edge dataset is depicted in Figure 6.



Fig. 6. Edge dataset example.

An edge image may contain regions with different levels of wear, which may make unreliable the classification using this dataset. Therefore, in a second step, a region dataset was created separating the vertical and horizontal wear edges (see Figure 7). In the end 577 regions with different wear levels compose the regions dataset.



Fig. 7. Region dataset example.

In this work, experts carried out two types of labeling: L-M-H (Low, Medium, High) wear and L-H (Low-High) wear. Note that the aZIBO is a shape descriptor, so images of the region dataset were binarized before computing it.

4. Experiments and results

Classification was carried out using: (a) kNN Leave One Out with five different distances: Cosine, Euclidean, Intersect, Chi-Square and CityBlock and (b) a Support Vector Machine (SVM) with a polynomial kernel of order 2 and Least Square algorithm as training method.

Two types of classification were carried out using the insert dataset: one considering three different levels of wear (low (L), medium (M) and high (H) wear) and the other considering two classes (low (L) and high (H) wear). kNN performance was assessed using k equals to 1,3,5,7 and 9, and the best results were achieved when $k=5$ in both cases.

In this paper, the performance of aZIBO was compared with two classical shape descriptors: Hu and Flusser moments.

In Table 1, performance for the L-H classification is shown.

Table 1. Inserts classification using aZIBO, Hu and Flusser descriptors for the two classes labeling (L-H).

	aZIBO	Hu	Flusser
kNN - Cosine	89.43%	80.07%	85.79%
kNN - Euclidean	89.60%	85.44%	83.88%
kNN - Intersect	89.08%	84.40%	81.46%
kNN - ChiSquare	91.33%	83.71%	83.19%
kNN - CityBlock	90.12%	85.10%	83.36%
SVM	88.45%	84.48%	75.86%

As it is shown in Table 1, the best results for the L-H classification are obtained using kNN with ChiSquare distance achieving an accuracy of 91.33%. Concerning the more challenging L-M-H classification, whose results are shown in Table 2, we have obtained a very interesting accuracy of 90.12% using the same configuration which achieved the best result with the binary classification, i.e. kNN with $k=5$ and ChiSquare distance. aZIBO outperforms in all cases Hu and Flusser.

Table 2. Inserts classification using aZIBO, Hu and Flusser descriptors for the three classes labelling.

	aZIBO	Hu	Flusser
kNN - Cosine	88.39%	78.37%	84.75%
kNN - Euclidean	88.73%	83.02%	82.32%
kNN - Intersect	88.21%	82.32%	80.07%
kNN - ChiSquare	90.12%	80.59%	82.50%
kNN - CityBlock	89.08%	82.84%	81.98%
SVM	85.52%	69.83%	53.28%

Figure 8 depicts the results obtained by aZIBO, Hu and Flusser in the kNN classification for different values of k and ChiSquare distance. L-M-H classification obtains results very similar compared with the binary classification, in spite of being more challenging. It is very interesting for the industry because the more number of different levels of wear they can distinguish automatically, the better planning they can do. Also, it is noticeable that aZIBO outperforms classical descriptors in all cases.

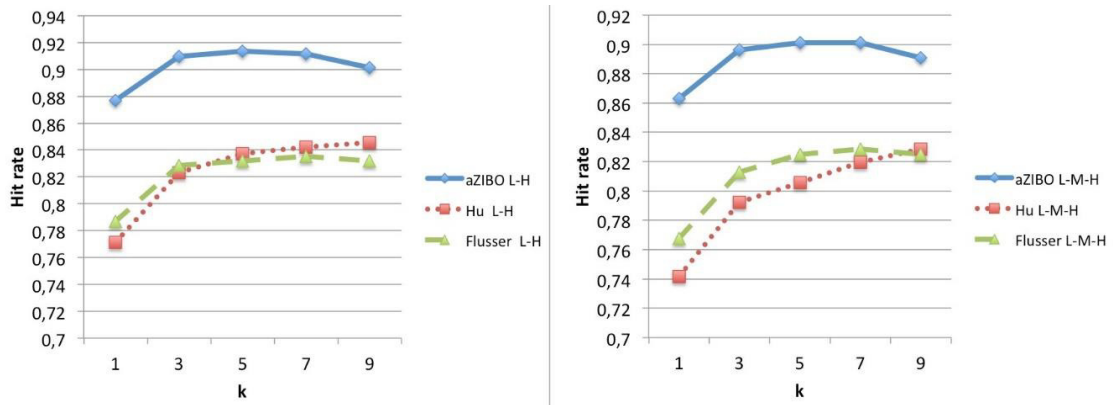


Fig. 8. aZIBO, Hu and Flusser classification using k-NN with different values of k and CityBlock distance in the L-H classification (left) and the L-M-H classification (right).

5. Conclusions

In this paper, a new dataset formed by 577 images with different insert wear was evaluated using shape description methods in order to automatically estimate the optimum time for tool replacement. Two well-known shape descriptors called Hu and Flusser moments were compared with aZIBO, a very recent method proposed by García-Ordás et al. [10]. Two different classifications, one binary and the other one ternary, were carried out using kNN with several distances and values of k . Results showed that aZIBO outperforms the classical descriptors in all the tests. In the binary problem, the best accuracy was 91.33% achieved with aZIBO, $k=5$ and ChiSquare distance. This hit rate improves the best results achieved by Hu and Flusser in 7.32% and 6.46%, respectively. In the Low-Medium-High classification, aZIBO also obtains the best results (90.12%), which is very similar to the one obtained for binary classification. This fact is very interesting taking into account the higher complexity of the ternary classification. In this case, aZIBO outperforms the best results of Hu and Flusser in 8.79% and 6.34%, respectively.

Acknowledgements

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