Estonian Journal of Engineering, 2009, **15**, 1, 3–12 doi: 10.3176/eng.2009.1.01

Use of contour signatures and classification methods to optimize the tool life in metal machining

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Received 28 July 2008

Abstract. Tool replacement operations have a great influence over the cost of machined parts. At present, the common criteria used to determine the tool life do not optimize the use of tools and lead to significant economic losses. The main objective of this work is to define a new procedure to improve the decision about the time for tool replacement. The approach followed is based on digital images of the cutting edge that has already been explored in the literature. The novelty of the present work relies on the use of contour signatures of the wear region as the input to two techniques of classification, k-nearest neighbour and a neural network. The influence of the signature size vector is also analysed. A total of 1383 flank wear images were acquired and the error rate estimation was about 5%.

Key words: tool wear, contour signature, neural network classification, tool life.

1. INTRODUCTION

The influence that tool replacement operations have over the cost of production in the scope of metal parts machining is highlighted by diverse authors [1–3]. This fact is especially important in production facilities, where high productivity level is required. The cost of tool replacement comprises not only the cost of tool inserts, but also the indirect costs associated with non-productive periods due to the tool replacement [4].

At present, the common criteria used to determine the time for tool replacement lead to the use of tool inserts only for a fraction of their possible useful life, both in manual and unmanned operations. In manual processes, tool replacement depends mainly on the machinist subjective criterion, which is based on experience.

In unmanned systems, the time for replacement is defined on the basis of accumulated values for some production variables (cutting time, amount of produced parts).

The previous tool replacement criteria do not optimize the use of tools. They lead to economic losses which can be significant in some applications. Wang et al. [5] indicate that measurement of tool wear to determine its usefulness can provide savings of 40% in tool costs.

The International Organization of Standardization (ISO) has included the consideration of tool wear in some standards, mainly for the economic implications which are derived from them. The approach adopted by ISO in the ISO3685 standard represents an advance with regard to the traditional industrial practice. This standard defines threshold values for the wear level to be measured directly over the worn area in the tool.

However, the main limitation of this approach is that these threshold values for wear are too conservative [6]. Also, measurement of the dimensions, indicated in the standard, is complex and requires interruption of the process.

The alternative method is based on the indirect measurement of wear. Implementation of indirect methods is very simple and does not require process interruption to evaluate the tool wear. However, the main drawback of these methods is poor precision and reliability of the measurements, mainly due to the presence of noise in acquired signals [6−9].

In contrast, direct methods are more reliable and offer higher accuracy of the measurements.

At the present moment, computer vision is a sufficiently developed technology. Its application to monitoring of cutting tools offers interesting possibilities as indicated in [3,5,7,10−14].

The main objective of this paper is to obtain the tool life using a computer vision system. The decision about the time for tool replacement (tool life) should be made taking in consideration a more realistic approach than the previous ones. Tool life is the period of time the tool is able to produce in-tolerance parts with regard to dimensions, geometry and roughness.

The approach followed in this paper is based on the analysis of digital images of the cutting edge to determine whether or not the tool wear is underneath the limit of use. Contour signatures of the wear region were used to describe each insert.

This approach, based on the use and interpretation of digital images, is not new. Some researchers have already used tool images to measure the wear. For example, Kurada et al. [8] use gradient and texture operators and apply them to digital images of worn tools; other authors [15−19] use vision techniques combined with neural networks; Wang et al. [20] use the well-known exponents of Lipschitz; Wang et al. [10] and Alegre et al. [11] use geometrical descriptors over tool images to classify the tool wear.

According to the followed approach, the metrics to be used is not specified *a priori*, but it emanates from data extracted from the observation of the tool wear phenomenon by means of digital images. The characterization of a wide group of wear regions through image descriptors, based on the contour signature, provides the support to an analysis of different wear states.

2. MATERIALS AND IMAGE PROCESSING

2.1. Materials and the machining process

Tests were done in a CNC parallel lathe. ANSI SAE 4340 and 4140 steel cylinders (tempered and normalized) were machined by turning. Dimensions of parts were 250 mm length and 90 mm diameter. Tools were tungsten carbide covered inserts (CNMG 120404 MF235), rhombic, high tough and low wear resistance, in order to avoid premature fracture and to increase the wear rate. Machining parameters were selected with the same objective: cutting speeds between 140 and 200 m/min, whereas feed rate of 0.2 mm/rev and cutting depth of 2 mm remained constant.

The tool was disassembled and inspected at the end of each machining path. The intensity of light and the focal distance were kept constant.

2.2. Image acquisition and processing

Images were acquired using a PULLNIX pe2015 b/w camera with 1/3" CCD. Digitalization was carried out with a MATROX METEOR II card. The optical system was made up of an OPTEM 70XL industrial zoom, an extension tube of 1X and 0.5X/ 0.75X/ 1.5X/ 2.0X OPTEM lens. The lighting system was composed of a FOSTEC DCR®III regulated light source and a SCDI system of diffuse lighting of NER SCDI-25-F0 to avoid shines. The lightening system provides diffused light on the same camera axis and its location was established by means of a FOSTEC quad bundle.

Image acquisition was carried out by using a specifically developed application composed of three modules: set-up of the camera, set-up of the sequence and acquisition of the image. These modules provide information of the capturing device and allow the user to choose the resolution, the storage path and save the images [11].

A total of 1383 tool flank wear images were acquired with this system. Each image was pre-processed, applying filters, improving contrast and cropping the region of interest [11]. An automatic segmentation was applied to obtain a binary image required later in the description step (Fig. 1).

(a) (b)

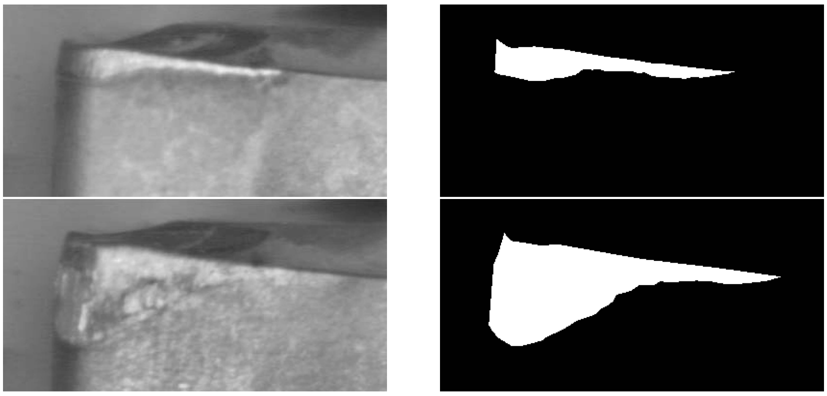


Fig. 1. Original (a) and segmented (b) images.

3. SHAPE DESCRIPTION USING SIGNATURES

A signature is a method that represents a contour using a one-dimensional function. A signature consists of a vector, where each element contains the distance from the centroid of the region to the pixels in the boundary.

A signature will be a good descriptor if it is invariant with respect to the location, size and orientation of the object in the image. The size invariant is achieved via signature normalization. With respect to location, our problem is not affected by location changes and treatment of this invariant is not required. However, an invariant to orientation signature is important since the starting point affects the shape of the signature. In order to obtain always the same starting point, the point nearest to the right-up corner of the image was chosen. This point is also a characteristic point of the wear region.

The signature is generated using the binary image of the wear region (Fig. 2a). Then, the region perimeter is obtained (Fig. 2b). The starting point of the signature is computed (Fig. 3). Finally, the coordinates of the centroid are calculated (Fig. 4).

(a) (b)

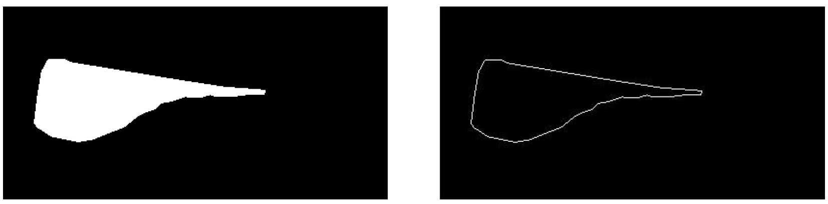
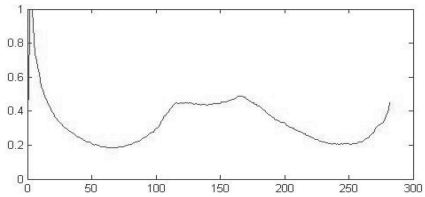


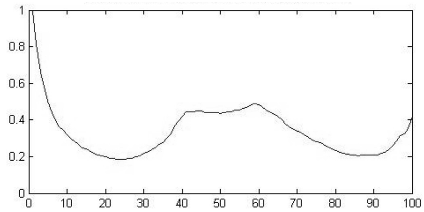
Fig. 2. (a) Binary image; (b) perimeter.

Fig. 3. Starting point of the signature.

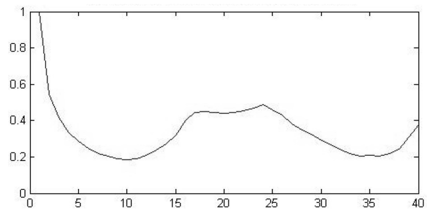
Fig. 4. Coordinates of the centroid.



Original signature



Resized to 100 values



Resized to 40 values

Fig. 5. Signatures.

The signature is computed as a vector, which contains so many elements as there are pixels belonging to the contour. Each element of the vector contains the distance between the centroid and the corresponding point of the boundary. Finally, the vector is modified to obtain 40 and 100 element vectors, which are normalized between 0 and 1. These modified vectors constitute the input to the classifier (Fig. 5).

4. EXPERIMENTAL RESULTS

A supervised classification has been carried out by labelling images according to two different criteria, defined in the ISO3685 standard. The first criterion was the V_{BB} value, which represents the average width of the wear band in the tool flank. The second criterion was the $V_{BC\max}$value, which is the width maximum value of the wear band in the tool tip.

Experiments have been carried out with 124 flanks and a total of 1332 images (545 with low wear and 787 worn).

Evaluation was carried out by 10-fold cross validation (sets split according to flanks) and the results are the average over five iterations.

The former feature vectors have been classified applying two different methods. The first one was the k-nearest neighbour (K-NN) with a 'random sampling' validation method and Euclidean distance. This makes it possible to compare the results, obtained with the K-NN classification, with those obtained with the neural network.

A perceptron multilayer neural network (MLP) was used with one node in the output layer. Tool insert is classified in two clusters: low wear and high wear. The optimum number of nodes in the hidden layer and the training cycles have been selected empirically. The learning algorithm belongs to the group of 'backpropagation' algorithms, in particular to the Levenberg–Marquadt optimized version.

The lower error rate, obtained with the $V_{BC\max}$ criterion (5.8%), was superior to that obtained with the V_{BB} criterion (5.1%). Table1 shows the errors obtained with the 100 signature vector using the MLP and different combinations of nodes and training cycles. The minimum error rate was 5.3% with 30 nodes in the hidden layer and 300 cycles.

Table 1. MLP classification based on the V_{BB} criterion and the 100 signature vector

Nodes	Number of training cycles				
	50	100	300	500	700
1	18.2	8.1	6.2	6.2	6.3
3	24.0	10.0	5.8	6.2	6.1
5	24.2	9.1	5.6	5.9	6.5
10	16.7	8.6	5.6	5.8	6.1
15	17.5	7.5	5.6	5.8	6.1
20	16.0	7.3	5.5	5.8	5.9
25	16.3	7.2	5.4	5.6	6.1
30	14.1	7.4	**5.3**	5.8	5.8
35	12.9	7.5	5.5	5.6	5.9
40	13.3	7.5	5.4	5.7	5.9
45	12.2	7.3	5.4	5.7	5.7
50	12.4	7.6	5.3	5.5	5.8
55	12.5	7.4	5.3	5.6	5.9

Table 2 shows the results, obtained with a 40 element signature, classified with the MLP and the V_{BB} criterion. It is noticeable that using the same classifier with 40 nodes and 300 cycles, the error rate (5.1%) is lower than in the previous case.

On the other hand, the error rates using the K-NN method with the 40 element signature are again lower than those obtained with the 100 element signature (Table 3). In this case, the minimum error rate (5.5%) is worse than the error returned by the MLP neural network.

With regard to the signatures used, Table 4 shows that an adequate classification is achieved with both signatures and the MLP neural network when comparing with the label provided. Label 1 means that the wear is not excessive and the tool belongs to class 1. When the wear is too high, the corresponding label is 0 and the tool belongs to class 2.

The assignment is wrong when using the K-NN classification. Table 4 shows that the result is wrong for the second flank image, which has label 1 but the assignment is to class 0.

Table 2. MLP classification based on the V_{BB} labelling criterion and the 40 signature vector

Nodes	Number of training cycles				
	50	100	300	500	700
1	21.1	9.3	5.6	5.9	5.8
3	31.8	10.1	5.7	5.7	5.9
5	26.3	8.9	5.3	5.6	6.2
10	28.2	8.2	5.4	6.0	6.5
15	23.2	8.4	5.5	5.9	6.6
20	18.9	8.2	5.5	6.1	6.7
25	16.7	8.0	5.4	6.0	6.4
30	16.1	7.9	5.3	6.0	6.4
35	15.8	8.0	5.2	5.8	6.5
40	15.0	7.8	**5.1**	5.7	6.2
45	14.2	7.6	5.2	5.9	6.6
50	15.3	8.0	5.2	5.6	6.4
55	13.9	8.0	5.1	5.7	6.2

Table 3. k-nearest neighbour classification and V_{BB} labelling criterion

k	Signature	
	100	40
1	8.0	9.2
3	6.4	7.2
5	5.7	6.2
7	5.8	5.8
9	**5.6**	5.8
11	5.6	**5.5**
13	5.6	5.5

Table 4. Wear level estimation according to the V_{BB} criterion and 40 and 100 signature vectors

Flank image label	MLP		K-NN	
	Signature			
	100	40	100	40
1	1	1	1	1
1	1	1	0	0
1	1	1	1	1
0	0	0	0	0
0	0	0	0	0
0	0	0	0	0
0	0	0	0	0
0	0	0	0	0
0	0	0	0	0

5. CONCLUSIONS

A new method to estimate the wear level in cutting inserts is proposed. Determination of the adequate time for replacement of the cutting tool is feasible using a computer vision system and a neural network classifier.

It is remarkable that description of the wear region by means of a signature vector with 40 elements is better than with a 100 element vector. Also, it is worth mentioning that with a MLP neural network the error rates are lower than those using the k-nearest neighbour classifier. Finally, the estimation according to the V_{BB} criterion is better than using the V_{BC} criterion.

Therefore the best option to estimate the tool life of inserts is combining the MLP neural network classifier, the 40 value signature and the V_{BB} criterion.

ACKNOWLEDGEMENTS

This work has been partially supported in the framework of the research projects DPI2006-02550 by the Spanish Ministry of Education and Science, ULE2005-01 by the University of León and LE018B06 by the Junta de Castilla y León.

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Kulumisjälje kontuuride kasutamise ja klassifitseerimise meetodid metallide lõiketöötlemisel püsivusaja optimeerimiseks

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Lõikeriista vahetusoperatsioonidel on töödeldud detailide maksumusele oluline mõju. Seni kasutusel olevad üldised kriteeriumid püsivusaja määramiseks ei

võimalda optimeerida lõikeriistade kasutamist ja see viib märkimisväärsete majanduslike kaotusteni. Antud uurimuse peamiseks eesmärgiks oli luua uus meetod lõikeriista vahetusaja määramiseks. Lahenduses on lähtutud lõikeserva digitaalsest kujutisest, mis on kirjandusest tuntud. Antud töös on kasutatud erisusena k-lähima naabri ja neurovõrgu jaoks sisendina kulumisjälje kontuure. Lisaks on analüüsitud kontuuri kuju ja suuruse mõju. Eksperimendis katsetatud 1383 kulumisjälje pildi puhul oli vea hinnang ligikaudu 5%.