Automatic segmentation of the wear region in cutting tools

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Abstract. This paper introduces a set of decision rules and a connected methodology designed to aid in the segmentation of the wear region caused in the cutting tool by the machining process. Every image undergoes a previous segmentation process that encompasses diverse techniques. If the cutting tool shows low wear level with this method a segmented region is obtained. Whether the cutting tool is highly worn or not is determined depending on the number of regions obtained with this previous method, the eccentricity and area. The darkest region caused by the curvature of the tip is obtained applying other algorithms from the images corresponding to those cutting tools that showed low wear level. When the wear region shows medium wear level, other methods provide the wear region. A set of 625 cutting tools were segmented and a visual check determined that the result was correct in 90% of the images.

Keywords: automatic segmentation, cutting tool, machining, extended-maxima transform

Introduction

One of the factors that have influence in the rentability of the machining processes is the cost of the cutting tool. Nowadays, the replacement of the tool is performed depending either on the subjective criteria of the worker or other criteria such as the machining time. During the last years various artificial vision techniques have been used to determine the wear level of the cutting tools objectively [1,2]. So as to estimate the wear level by means of digital images the wear region must be obtained first. Due to the difficulties involved in performing a totally automatic segmentation [3], current research is based on manual or semi-automatic segmentation methods [2]. In this paper we present an intelligent method that performs an automatic segmentation of the cutting tools wear region.

The set of images under analysis comes from various turning tests using three different steels. A series of images were obtained ---625 in all--- for each type of steel from 65 cutting edges.

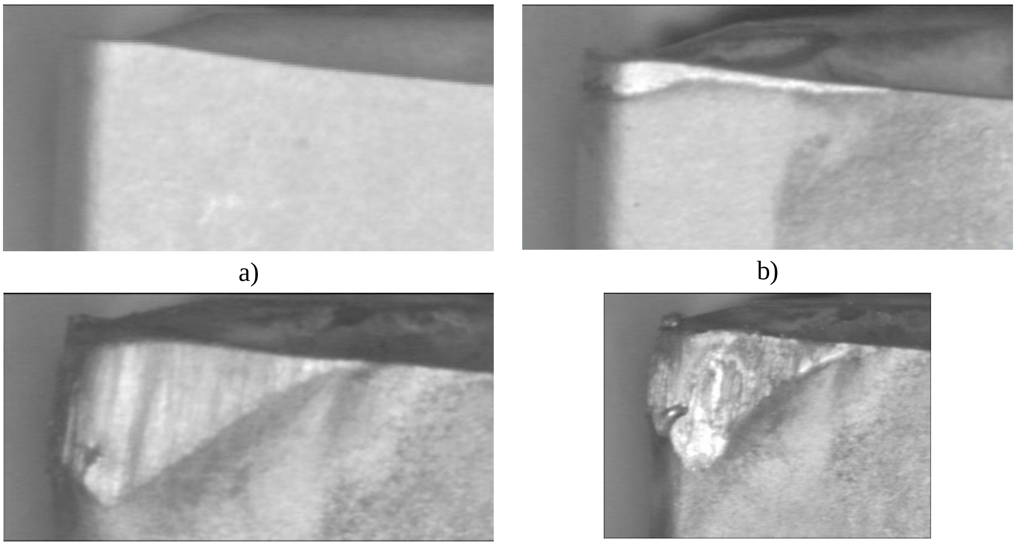
The automatic segmentation method developed is based on the combination of different techniques: thresholding, first and second order filters for edges detection, morphological operations, the extended-basic transform and a set of decision rules that identifies whether the different segmentation algorithms obtain the expected results or applies other algorithms otherwise.

Automatic segmentation of the wear region

Cutting tool condition and different types of segmentation. Despite the fact that the purpose of the segmentation is just to determine correctly what pixels belong to the wear region, the condition of the cutting tool makes methodology to be different. In our case, we have detected four different types of images and we have applied different techniques to segment the first three types (see Figure 1):

- Original images (undamaged).
- Low wear level images.

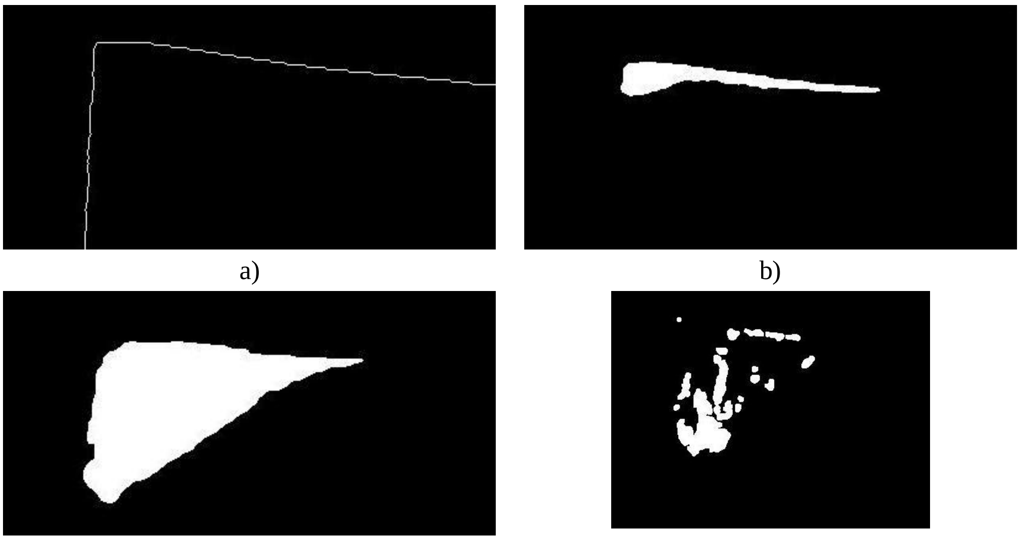
- Medium wear level images.
- High wear level images.



a) b) c) d)

Figure 1. Different types of wear. a) Original images (undamaged). b) Low wear level. c) Medium wear level. d) High wear level.

Although segmentation does not provide a classification, as it does not provide a quantitative measurement of the wear, it can be seen that there is a correlation to a certain extent with the findings of other researchers as Sick [4], that classifies wear in two levels ---apt and nonapt--- or Guo et al. [5], that consider three different wear levels. As in the former, it could be thought that the first two types of images belonged to the apt level, the four to the nonapt level whereas the third type would probably have both types of images. According to the latter, the images from types a) and b) would belong to the first class and, most likely, those from c) to a second and those from d) to a third.



a) b) c) d)

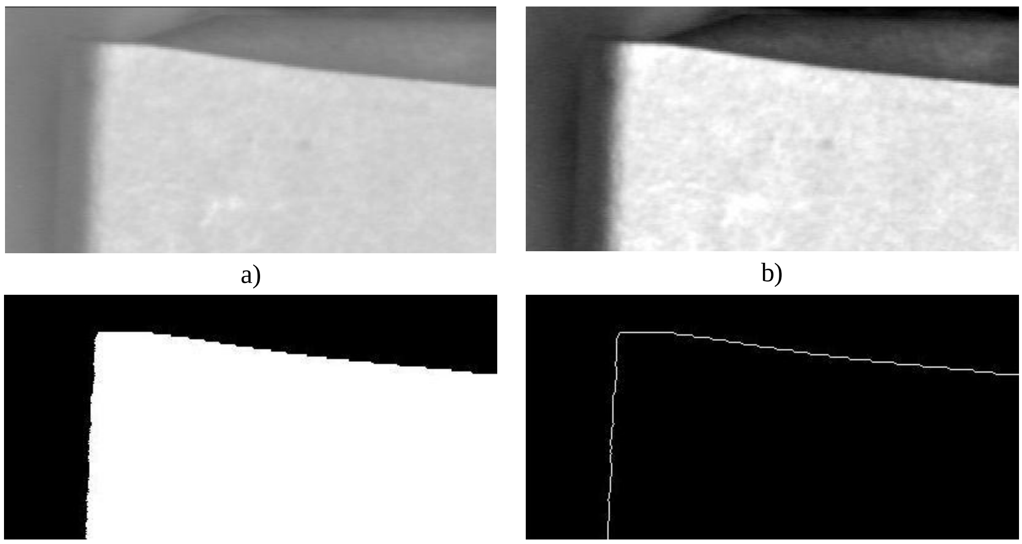
Figure 2. Segmentation obtained at different wear levels a) Original ---undamaged---. b) Low wear level. c) Medium wear level. d) High wear level.

The results from the segmentation can be seen in Figure 2. We explain them in detail in the following subsections.

Undamaged cutting tools. Segmentation of the tip. Apparently, it could be thought that there is no need to segment the original images ---undamaged--- as no sign of wear is present. Instead, we have considered them because due to the lighting conditions a dark band not coherent with the curve of the tip appears. After some wearing, the methods used did not detect that band, and the information about its geometrical features would be lost otherwise. Thus, we use the original cutting tools —undamaged— to detect the width of the dark band and to add the segmentation of that region with that obtained by means of the algorithms used for detecting the wear of the flanks.

Before applying the process that we are about to explain, every cutting tool is previously segmented by those methods explained for cutting tools with low wear level. If no white region appears at the end of that processing, then that image is labelled as “undamaged” and the next procedure is applied.

Figure 3 shows the result of a first segmentation of an original image (Figure 3.a). First, the histogram is stretched (Figure 3.b) allowing the use of the extended-maxima transform [6] and obtaining the results that Figure 3.c shows. Finally, a high pass filter and some preprocessing operations provide the image that can be seen in Figure 3.d. It can be seen in this figure that the edge corresponds to the limit of the clear area in the flank of the cutting tool, not including the darkest region of the tip.



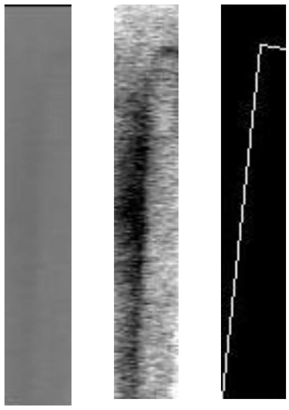
a) b)

c) d)

Figure 3. Images obtained at the intermediate phases during the segmentation of the undamaged images.

Then we apply another specific processing to detect the dark band of the tip. First, we automatically crop a band 40 pixels wide and a number of rows slightly superior to the length of the vertical edge of the cutting tool that appears in Figure 3.b. The size of the band depends on the size of the captured images. In our case, that band always included the shaded region of the tip (Figure 4.a).

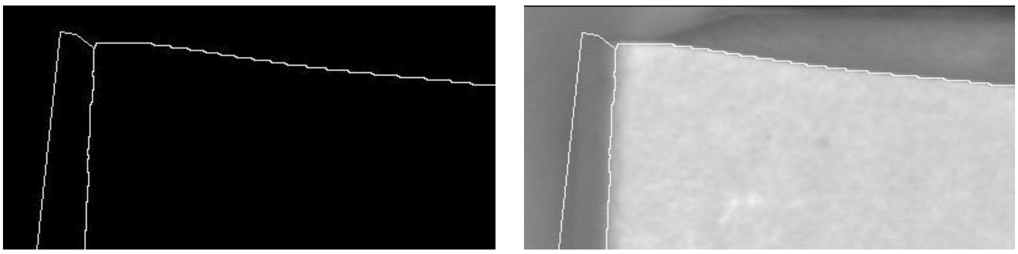
Afterwards, the histogram is stretched (Figure 4.b) and then a set of procedures, amongst which a high pass filter to detect vertical and horizontal edges is applied. Later, the small regions and those not in contacts with the edge are removed so as to obtain just the horizontal top edge of the band. Then, a set of morphological and thinning operations provide us a clean horizontal top edge. Finally, the location of the pixel where the shade intersects the lower region of the image and gets connected with the upper right end of the top horizontal edge is obtained by means of the Bresenham algorithm.



a) b) c)

Figure 4. Segmentation of the shaded band of the tip

Figure 5.a shows the edge obtained for the shaded region while Figure 5.b shows the edge previously calculated for the flank of the cutting tool plus this latter edge, overlapped with the original image in greyscale.



a) b)

Figure 5. Edge of an undamaged cutting tool. It comprises the edge of the flank and the edge of the shade band of the tip.

Low wear level cutting tools. The following method is applied to every cutting tool. Depending on the number of resulting regions and other properties of these regions —as their area and eccentricity— will be applied either the methods for original cutting tools or those for medium wear level cutting tools. Figure 6.a shows the original image while Figure 6.b shows the image after stretching the histogram.

Then, an extended-maxima transform is applied with a threshold of 50 (Figure 6.c). Later, an edge detection, hole filling and morphological closing are performed. After removing the regions that are in contact with any of the borders we obtain the image showed in Figure 6.c. As only one region appears, and its eccentricity is bigger than 0.9, it can be considered that the first phase of the segmentation for this image is completed.

So as to include those pixels located next to the border that also belong to the wear region, a growth of regions with pixel aggregation is performed (Figure 7.a). The final result, before obtaining the wear region located at the tip, can be seen in Figure 7.b.

Medium wear level cutting tools. In case that in the previous stage the image resulting from the first segmentation phase either contains more than one region or its eccentricity is lower that 0,9, the image undergoes the following procedure.

Figure 8.a shows an example of an image with medium wear level and the same image after stretching the histogram (Figure 8.b). Figure 8.c shows the result after applying the extended-maxima transform with a threshold of 67. Afterwards, the regions in contact with the outer border are removed, the holes are filled, a morphological closing is performed and those regions considered as very small are removed.

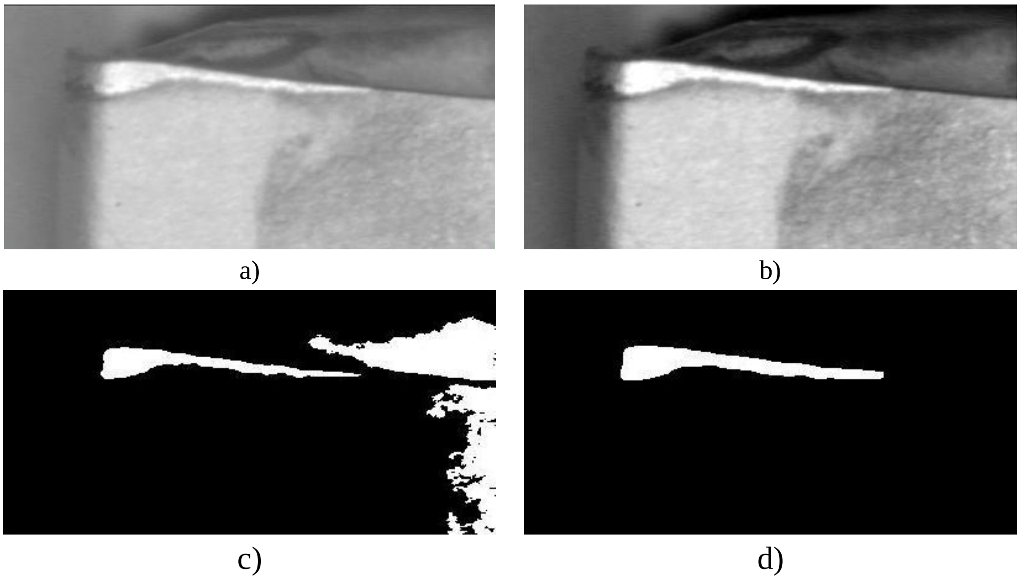


Figure 6. Images obtained at the intermediate phases during the segmentation of the low wear level images.

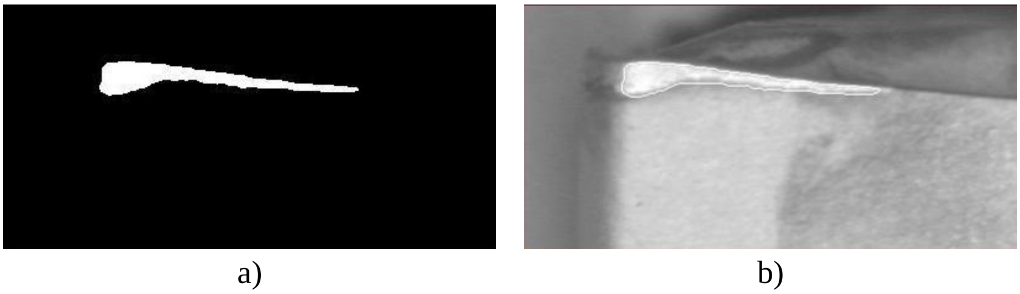


Figure 7. Final segmentation of the low wear level region after the region growth and the visual check of that segmentation without including the tip region.

Then, the region or set of regions obtained are studied. In case that the region eccentricity is lower that 0,79 or two regions appear, the wear of the image is considered as high and no further segmentation is performed since no measurement of the wear is pursued.

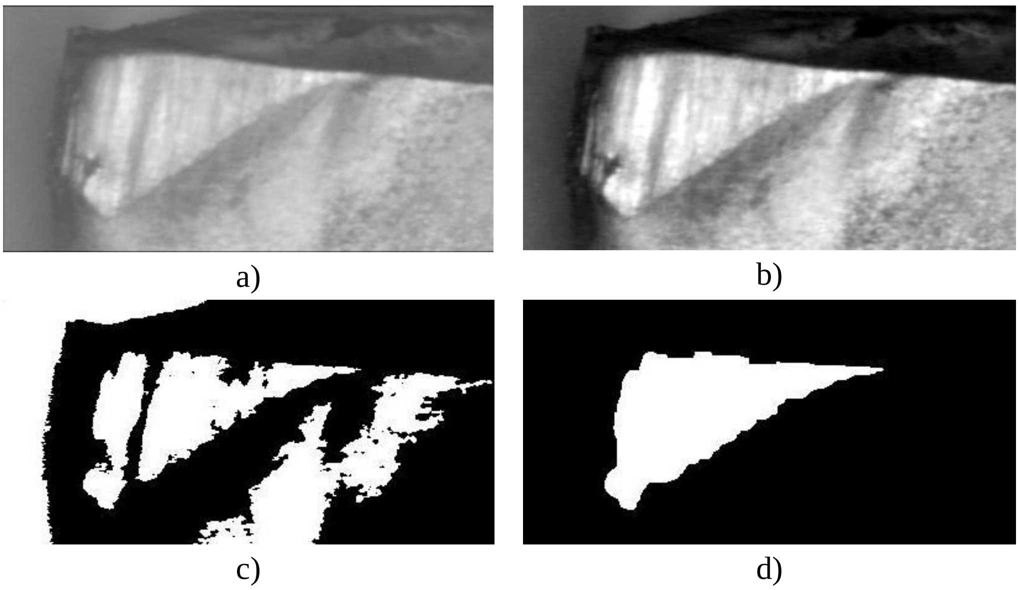
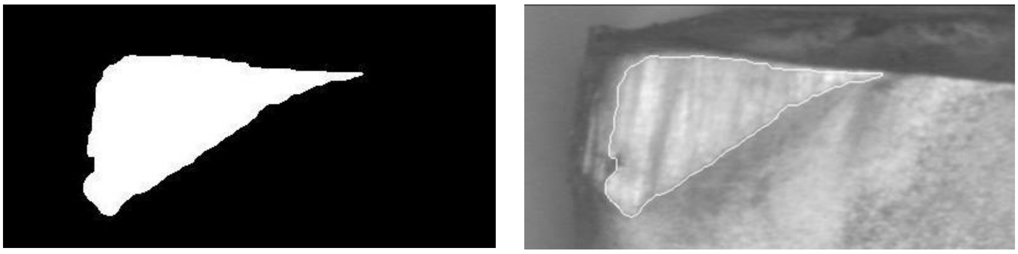


Figure 8. Images obtained in the intermediate phases during the segmentation of the medium wear level images.

In case that after performing the above mentioned analysis the wear of the image is considered as medium, a region growing by pixel aggregation is finally performed whose results can be seen in Figures 9 a and b.



a) b)

Figure 9. Region obtained from the segmentation of medium wear level cutting tools.

Results and Discussion

The main result we have obtained is the correct segmentation of 90% of the wear regions out of the 625 cutting edges under study. We do not include in this percentage those images with high wear level that were not segmented. The method validation has been visually performed. In case that the methodology were applied in an on-line wear monitoring system, the segmentation of this kind of regions would not be needed since the cutting tool has to be replace before reaching this status. In case that the monitoring system would not identify that region as nonapt, the very segmentation process would help in perfectly identifying that kind of wear, thus making the cutting tool to be replaced.

Conclusions

The presented method allows segmenting the wear region of those cutting tools with low and medium wear level. It is an ad-hoc method developed for cutting tools but just with small modification it can be adapted to other tools with similar geometry. It has been solved the difficult problem of the segmentation at the tip caused by bad lighting conditions.

Acknowledgements

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