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ASSESSMENT OF CUTTING TOOL WEAR USING COMPUTER VISION

Breno Barros Costa
Universidade Federal de Minas Gerais, Av. Pres. Antônio Carlos, 6627
brenobc@ufmg.br

Alexandre Mendes Abrão
Universidade Federal de Minas Gerais, Av. Pres. Antônio Carlos, 6627
abrao@demec.ufmg.br

Pedro Bastos Costa
Universidade Federal de Minas Gerais, Av. Pres. Antônio Carlos, 6627
pedro@demec.ufmg.br

Antônio Augusto Torres Maia
Universidade Federal de Minas Gerais, Av. Pres. Antônio Carlos, 6627
aamaia@demec.ufmg.br

Abstract. *In the traditional approach to determine tool wear in machining operations, the cutting tool is removed from the machine tool and tool wear is evaluated by the operator. This procedure demands time and human intervention, and the results can be significantly influenced by the operator. An erroneous evaluation may lead to wrong decisions that can compromise the quality and efficiency of the manufacturing process. An alternative is to evaluate tool wear inderrectly during the manufacturing process by using image metrology. This procedure can be automated using algorithms and systems for image acquisition and analysis, thus providing a fast method for wear measurement using a standardized procedure. This work aims to present the development of a computer vision algorithm to evaluate the wear of cutting tools through image analyses. The procedure for tool wear measurement encompasses image acquisition and recognition, morphological transformations, edge detecting, and wear measurement. In this work, the acquired image with both a reference object and the worn cutting tool is processed by the software, firstly determining the number of pixels that the width of a reference object occupies in the image, since this width is known, a scale factor relating pixels to linear length can be determined. The next step is obtaining the number of pixels containing the wear land of the cutting tool, using the scale factor the pixels are converted to linear length. Preliminary results indicate that the maximum flank wear measured with this method presented an accuracy from 0,99% to 4,90%. It was also noted the feasibility of using a unique scale factor, avoiding the need of reference objects for each image extraction. It was noticed that a standard scale factor is effective for different measuring experiments since the tool is located at the same position and the images are acquired preserving the same conditions such as distance of the tool from the camera and lighting. The data provided by the system can be used to expand future research in the field of machining, avoid machine and tool holder damage caused by catastrophic tool failure, determine the time to replace cutting tools with better accuracy, reduce rejected parts and increase productivity.*

Keywords: *Computer vision, image metrology, measurement device, cutting tool wear, wear measurement*

1. INTRODUCTION

Progressive tool wear is unavoidable in machining operations. The evaluation of the magnitude of this wear can be used to indicate when the tool should be replaced, if the exchange is not carried out at the correct time, either the quality of the produced part may be compromised or the nonproductive time may be increased, Pavim (2005).

According to Pavim (2005) tool wear evaluation is performed by measuring the worn region using a toolmaker's microscope, which requires the removal of the tool from the holder and taking it to the measurement device to proceed with the evaluations. This process requires considerable downtime to perform the measurement and can result in significant losses with the reduction of the productivity of the equipment. A point of improvement in the process would be the automation of the wear measurement directly in the equipment to determine the exact moment when the cutting tool must be changed.

Using image recognition algorithms, flank wear measurement can be carried out, Thakre, Lad, Mala (2019). With tool wear being carried out in an automated way, this parameter can be evaluated more frequently, thus assisting research in the machining area and removing external factors that could influence tool life measurements.

A better definition of the right time for the tool replacement can contribute to reduce costs and increase productivity. In an environment where the connection of machines and the world wide web is increasing, the data acquired during the tool monitoring can be integrated into the company data center and be used to plan the machine maintenance and supply chain. In this context, this work aims at evaluating the wear in cutting tools by computer vision using an algorithm that acts in an automated way, and defining a methodology for using a single parameter for the scale factor.

2. COMPUTER VISION THEORY

Computer vision is a field of science that works with digital images to automate decision-making by operators and users. Systems using computer vision are based on methods of acquiring, processing and analyzing digital image data. In this field, the programs developed seek to identify objects and patterns in the images that allow classifying the elements or obtaining information about the components present in the images. These vision systems are mostly intended to simulate human vision in specific applications, Azevedo (2013).

In order to obtain the Region of Interest (ROI), an auxiliary image is created, which consists of a binary matrix with the same dimensions as the original image, which is composed of 0 (zeros) and 1 (ones). To accomplish this conversion, the use of thresholds is common practice, Pavim (2005). In the case of three colored images, three parameters can be used. As each parameter can have a lower and an upper limit, there are six free variables to be selected. In the case of grayscale images there is one parameter to be used, in the same way an upper and lower value can be defined, thus generating two free variables.

This threshold method is used to highlight the region being analyzed from the background. This analysis can be based in pixel luminosity, defining a threshold, upon which higher values are considered as part of the ROI, and lower values as rejected. Equation (1) represents how this evaluation is made for an 8-bit grayscale image, Costa (2012).

$$g(x,y) = \begin{cases} 1 & if\ \ T_{inf} < f(x,y) \leq T_{sup} \\ 0 & if\ \ T_{inf} \geq f(x,y)\ ou\ f(x,y) \geq T_{sup} \end{cases} \quad (1)$$

Thakre, Lad, Mala (2019) used the calibration factor for the pixel considering the horizontal and vertical components. Following Equation (2) for the horizontal direction and Equation (3) for the vertical direction.

$$Px\ (mm/pixel) = \frac{lenght\ in\ x\ (mm)}{number\ of\ pixels\ in\ x\ (pixel)} \quad (2)$$

$$Py\ (mm/pixel) = \frac{lenght\ in\ y\ (mm)}{number\ of\ pixels\ in\ y\ (pixel)} \quad (3)$$

Dai (2018) and Pavim (2005) identified that the directional measurement at x and y showed negligible differences. Therefore, the above equation can be generalized for the orientation that the reference object is found, according to Equation (4).

$$P_{\theta}\ (mm/pixel) = \frac{lenght\ in\ \theta\ (mm)}{number\ of\ pixels\ in\ \theta\ (pixel)} \quad (4)$$

3. TOOL WEAR INSPECTION METHOD

According to Klocke and Kuchle (2011), the most referred tool wear parameter to monitor machining processes is the flank wear. Figure 1 shows the regions of the tool where wear occurs. The wear that can occur on the clearence face are VB_B: avarege flank wear, $VB_{Bmáx}$: maximum flank wear and VB_n: notch wear.

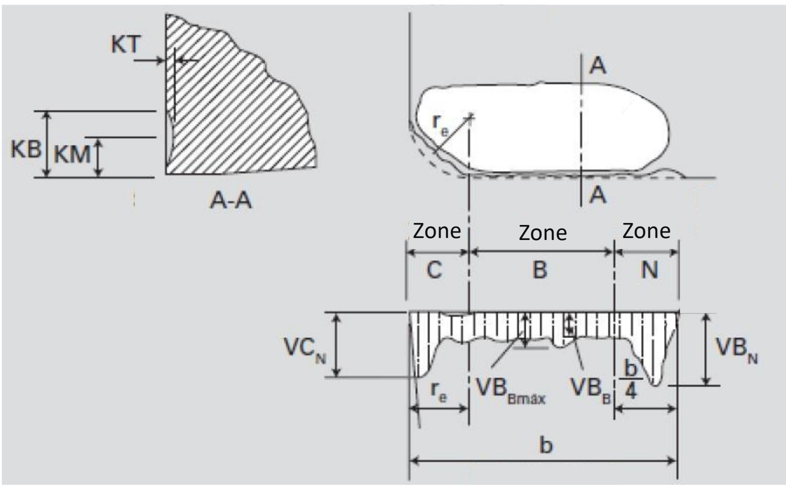

Figure 1. Tool wear parameters. Machado et al. (2009)

The tool wear inspection was carried out using the experimental setup shown schematically in *Figure 2*. The setup is equipped with an 8 Mpx camera, a 9 W LED light as a main light source, and a Raspberry PI 3 model B as a logic board to process the data.

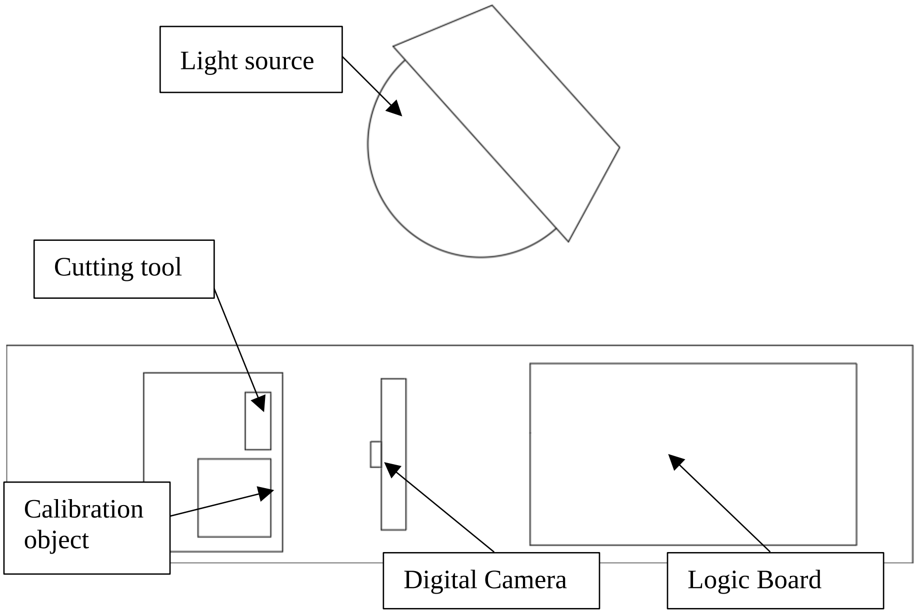

Figure 2. Schematic of the measurement prototype

According to Dai (2018), Schmitt, Cai, Pavim (2012) and Pavim (2005), the use of grayscale is widely used for cutting tool wear measurements. Although Tang (2020) and Huang (2011) use HSV measurement in other applications, it was noted that its application for tool wear measurement does not produce satisfactory results, according to Pavim (2005).

The software developed in this work employs images acquired in grayscale and runs on the Raspberry Pi logic board with a program coded in Python 3 language. The program was written using the OpenCV library, which has features for implementing machine vision. This program was selected because it is compatible with the logic board and the available libraries for image processing.

During the experiment a precisely drawn square was used as a measurement reference, it was measured in the same image as the cutting tool. This reference is necessary to evaluate the pixel size in the current setup. The wear parameters are measured by the software considering the pixels occupied in the image then these parameters are converted to linear measurements by the pixel size.

A critical point for the realization of the project was lighting the system. Using only ambient lighting, evident tool wear was not identified. The absence of light intensity gradients meant that the region of interest was not correctly identified in the software. In one of the evaluated lighting modes, the additional light source was positioned laterally in the setup, so that it does not appear direct in the image and there are no directly reflections to the camera, since the cutting tool can be reflective. This configuration allows the predominant lighting to be controlled avoiding influences of external lighting and enables the software to identify the wear region. The use of a clear background for the setup was also considered, but after some tests a darker background performed better at edge detection.

Before the acquisition process starts, a calibration procedure was executed. A raspberry pi camera module V2, with a resolution of 3280 × 2464 pixels, was selected for the assembly. A specific acquisition procedure was performed for the cutting tool and the measurement of the calibration square. Favorable conditions of positioning and parallelism were used, thus the contours between the surface of interest and the background were well defined and the measurement surfaces were flat with respect to the camera. Between each measurement the calibration squares were removed and repositioned in the assembly. Therefore, the system was tested against changes in the positioning and the behavior of the software was evaluated under these conditions. The addition of variability in computer vision systems is necessary to reduce conditions that can lead to trends in the variables to be measured. The measurement relied on a stepwise reduction in dimensions from 10 x 10 mm to 1.0 x 1.0 mm.

The developed software was designed to perform all the necessary steps for measurement. Therefore, a single program performed the image acquisition and the flank wear measurement, making the system autonomous. The diagram shown in *Figure 3* indicates the sequence of operations performed by the software to conduct the wear measurement. The software operates in two phases, firstly obtaining the pixel size and secondly to evaluate the wear parameters. The acquired images were processed autonomously by the software and exported to a file. This file was later assessed using an image processing software and the measurements by both methods were compared.

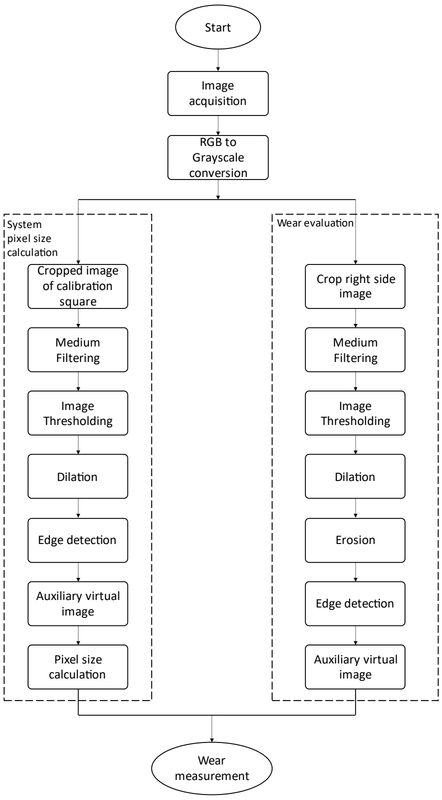

Figure 3. Flowchart of the algorithm for image processing.

Initially, to perform the wear measurement, the known dimension of the reference object must be informed to the software. This dimension is responsible for calculating the pixel size conversion factor. The image obtained is then cropped in the middle to separate the processing into two evaluations. The square used as a reference is on the left-hand side and the tool with the wear to be measured is on the right-hand side. The software begins with determining the pixel size value by treating and processing the data from the square side to evaluate the pixels occupied by the square in each direction. This pixel length, alongside with the known dimension of the square were combined to calculate the pixel size. Figure 4 is an example of an image obtained by the setup, it shows the square positioned at one side while the cutting tool on the other side of the image.

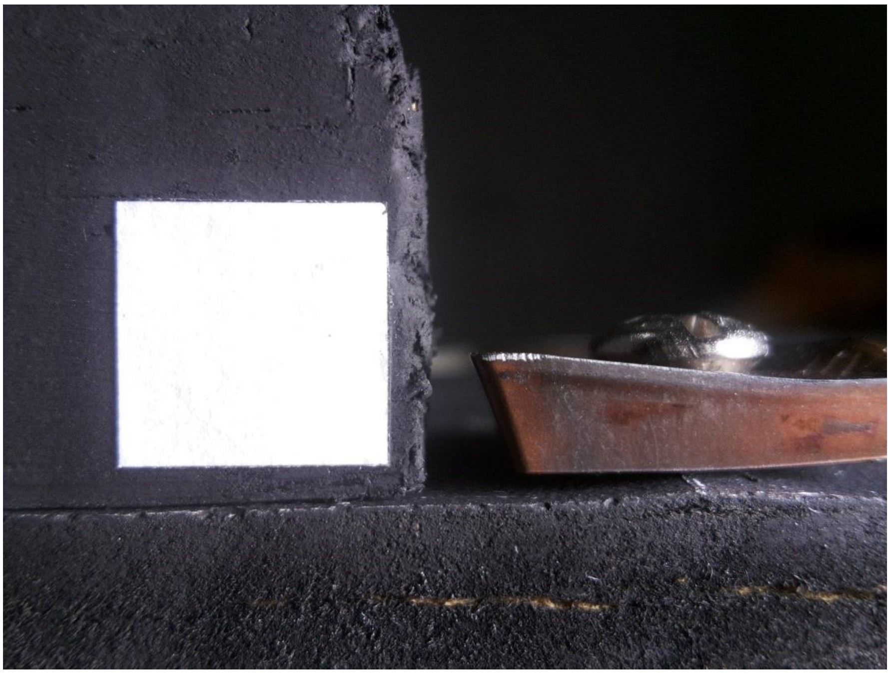

Figure 4. Captured image of the square and the worn-out insert

The cropped right-hand side of the images contains the cutting tool and the wear region. In order to allow the software to correctly identify the tool wear, the zone of the image containing the wear was amplified. To highlight the wear region a threshold method was implemented, which was the first step to allow the software to perform the post treatment image processing. This threshold was obtained by adjusting the value that correctly identified the wear zone.

The measurement method was evaluated on calibration squares and on cutting tools. For each configuration, 10 images were acquired. The focal distance of the camera was 28 mm, which resulted in a horizontal range of 34 mm. In this configuration the pixel size was close to 0.010 mm / pixel. This focal distance was chosen after some measurements, it was noticed that there is a trade-off at changing the focal distance. The shorter the distance from the camera to the object, the smaller the pixel size, which could provide a better accuracy and resolution to the system. However, with short distances the image tends to be blurry, which results in an accuracy loss.

It was noticed that the variation in the pixel size had a low deviation over each experiment. This motivated the evaluation of standard pixel size for all experiments. The pixel size of the experiments was averaged and the standard deviation was calculated to determine if this method was feasible.

4. EXPERIMENTAL RESULTS

The results obtained for the measurements of the printed squares were shown in Table 1. Using the actual value of the reference square, the relative trends were obtained. It is possible to observe that the obtained trends decreased proportionally with the increase of the measured values.

Table 1. Comparison between reference values and those obtained by the machine vision system

Experimental value (mm)	**Software result (mm)**	**Deviation (%)**
1.0	0.98	1.70
2.5	2.47	1.20
5.0	4.97	0.58
7.5	7.53	0.42
10.0	10.0	0.31

When evaluating the results obtained, it was observed that the values presented for the measurement of the squares are close to the actual measurements, and when analyzing the absolute values no pattern was noticed among the results. It was only when analyzing the relative deviation that a trend in the results was identified, for the smaller objects a loss of accuracy in the results was noticed, with the error ranging from 0.31% for 10 mm to 1.70% for 1.0 mm. This may have happened since an incorrect classification of one pixel generates a greater relative error in smaller objects.

With the validation of the previous steps, the final step was taken to measure the maximum flank wear of the tool. For the manual wear measurement, the wear values for tool “A” were obtained as 0.32 mm and for tool “B” 0.47 mm. With the support and validation of the wear region identification step, it was possible to obtain the wear values of the tool by the software. The evaluation is presented at Table 2.

Table 2. Comparison between the average wear width measured by the vision system and manual measurement

Tool (mm)	**Manual measurement result (mm)**	**Software result (mm)**	**Deviation (%)**
A	0.320	0.323	1.0
B	0.465	0.442	4.9

Subsequently, it was possible to conclude that the measurement by computer vision proved to be valid in measuring the wear of cutting tools, obtaining a maximum error of 4.90% and a minimum error of 0.99%. It was noticed that the irregularity of the wear on the cutting tool influences the errors obtained, but even with the irregularity, parameters can be adjusted in the software to obtain consistent results.

Figure 5 shows the wear regions detected by the software highlighted in black, where $VB_{Bmáx}$ is the distance indicated by the red arrow. In figure a) the cutting tool A is shown, while figure b) shows the cutting tool B.

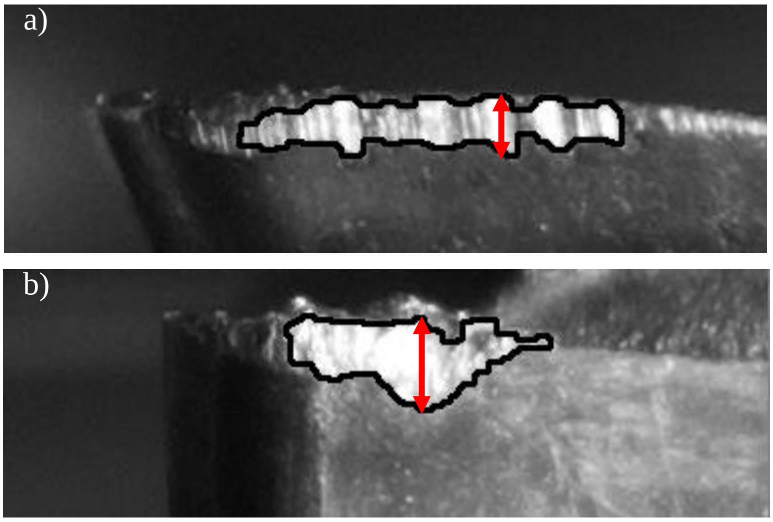

Figure 5. Results of edge detection on the cutting tools; a) Cutting tool A, b) Cutting tool B

On evaluating the use of a reference pixel size from the data of these experimental values, the average pixel size obtained experimentally for the squares was 0.0104 mm / pixel with a standard deviation of 1.32%. Considering this deviation in the scale factor, it was considered that it is feasible to use this system with a standard scale factor. This consideration reduces a measurement parameter in the system, which prevents loss of accuracy over continuous use and does not require the replacement of the calibration square after in the machine equipment.

5. CONCLUSIONS

Using the software to obtain the wear region, it was evaluated that the identification of the wear region by this system was coherent with the wear identified by the operator, also, the values obtained by the computer are compatible with the results of the manual measurement. This reinforces that the tool wear inspection can be performed by a computer vision software.

For the purpose of defining the moment to replace the cutting tool in a machine equipment for a new one, or to obtain data for further studies of tool monitoring, the accuracy obtained by the software is enough to evaluate the operational conditions of the cutting tool. Since the wear region can presente irregularities, the deviation presented by the system could be an imprecision of defining the pixels of the ROI.

It was also noted that the software was calibrated for the cutting tool A and with the same parameters the software correctly identified the wear region for the cutting tool B. This indicates that this system can perform consistent measurements through a range of cutting tools if the parameters are properly calibrated.

For the measurement of tool wear by the software it was noted that some settings are needed to ensure the correct results from the software. Since the ROI is obtained through light intensity, the most relevant setting is the lighting directed to the cutting tool, the influence of external light can be reduced if a strong direct light is present in the setup. As the camera does not measure depth, a criteria that needs to be accounted for is the parallelism of the camera plane, the plane of the reference square and the wear region plane.

Overall, the presented method showed a good performance in cutting tool wear measurement and can be used to perform tool monitoring in machine equipment.

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