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MONITORING MACHINING TOOL WEAR ON PLATFORM LABVIEW USING MACHINE VISION

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Abstract. *Machine vision systems have been used for monitoring of the cutting tools as a preventive measure and avoid loss the premature insert. The National Instruments (NI), hardware PXI and LabView program also have been used for it. This study aimed to develop software for image acquisition and processing to identify damage and flank wear on machining tools. The program will classify two insert classes, which separates wear flank and damage, so if insert is classified like damage, it will be discarded immediately, if not the program run to measure flank wear. The development of the classification phase was used 200 flank wear and 23 damage images insert from the University of Florida (UFL). Texture analysis techniques and Bayesian method were used to classify the inserts in the two classes, damage or flank wear. The next step was measure VBmax. Sobel filter was the best solution to edge detection. The function block IMAQ Clamp Horizontal Max VI was used to measure the flank wear maximum. The image acquisition was used a Vimicro camera, PXI USB, the Vision and Motion Labview library . The system and image processing were tested with four inserts (16 images) from the Federal University of Uberlândia (UFU). Microscope image were used for validate accuracy of the system. The Kappa coefficient to evaluate the classification between the damage and the flank wear, from the UFL images, was 82.2%. The accuracy of measures Flank Wear Maximum, from UFU images, was 95.5%. The program developed in LabView platform and PXI-NI proved acceptable for acquire, process and monitor images worn insert.*

Keywords: *Tool wear, cutting tools, machining, coated carbide insert, industrial image processing*

1. INTRODUCTION

Businesses seek to achieve efficiency in its manufacturing process by reducing the amount of waste parts and improved quality of manufactured products. For this purpose they are used preventive methods of monitoring the process to avoid an error during manufacturing (König, 1981).

The machining process is the most widely used process for the manufacture of products (Bombonato et al., 2008). Much research is primarily focused on its monitoring, where the identification of damage and measurement wear flank, thus extending the life tool and increasing the quality of the process.

Automated monitoring has numerous advantages over a human monitoring, mainly speeds, lack of subjectivity and avoids lost time for stop machining to check and tool wear measure. The machine vision is a process and analysis of images to identify patterns in region of interest (ROI), instead the use the vision human for it. The maximum flank wear is a patterns widely used to replace cutting tool. However, this measurement is time consuming if done manually. The current, automated processes systems are limited to large companies, due to the high costs demanded. Due increasing speeds and the decreasing price of computers, machine vision systems have popularity in the measuring tools in many application areas. Thus, much research has been conducted on using image processing, including for measuring tool wear.

The LabVIEW platform provides an extensive library of routines for the acquisition and processing of digital images. The hardware (PXI) from National Instruments (NI) is using to process the LabView program.

The chassis allows of the attach modules for image acquisition and automation. This makes it easy for develop and optimize control systems..

This study aimed to develop a software for image acquisition and processing to identify damage and measure wear flank on machining tools using the library and LabView program in NI chassis.

2. MATERIAL AND METHODS

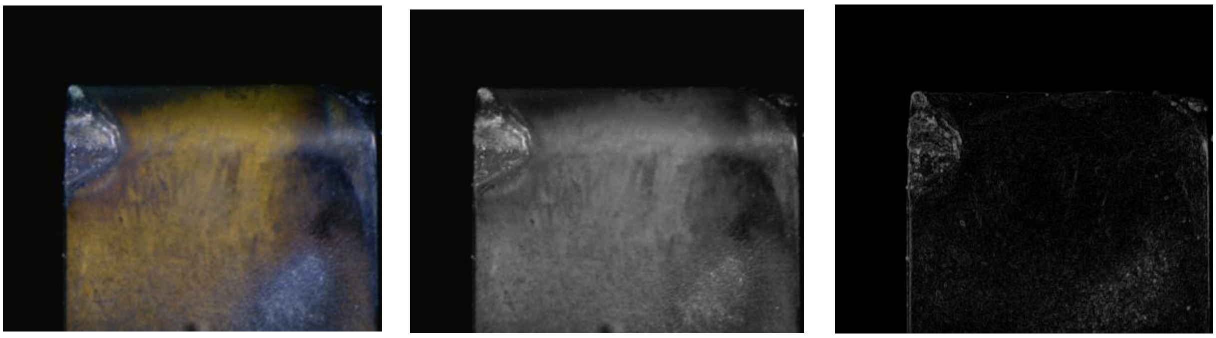
The phase of the development classification program were used 201 flank wear and 22 damage image inserts from the Manufacturing and Innovation Center of the Department of Mechanical and Aerospace Engineering at the University of Florida (UF), obtained through a Dino-Lite microscope camera (Dino X Lite - AM413 TX) with LED illumination. The image was 1600 x 1200 pixel with a space resolution of the 7.5 micrometers (3387 dpi).

In order hand, to test the acquisition system and measure the wear flank were acquired 16 images of two inserts worn from the Federal University of Uberlândia (UFU). A Vimicro camera, USB cab, PXI-NI hardware, and the Vision and Motion LabView library were used to acquire this image from UFU.

2.1 Definition of region of interest (ROI)

An important step is determined the region image to be analyzed where processing is concentrated, avoiding possible errors caused for analyze all image.

A model image processing RGB (Red, Green, Blue) shows unsatisfactory results when the enhancement is from three RGB components. Other color models like the HSI (Hue - Saturation - lightness) are most suitable for the purpose of gray image processing, since the lightness component represents the intensity of the image, since this model has the component representing the intensity of lightness. The determination of the ROI began in the image of the change to grayscale, with the extraction component of luminous intensity from HSI image. Figure 1 (A) and (B) shows this first step. After change original image to grayscale image applied an edge detector filter. According to Gonzalez and Woods (2000), this is a process for enhance edge line between two regions with different properties in respect of gray level. The edge detection filter was applied by derived type, using convolution masks, also named operators. The Sobel operator (3x3) derived in vertical and horizontal directions, and has focused in the points near to the central pixel. The Sobel operator gives the advantage of providing, at the same time the purposes of enhance and smoothing. How the derivate increase the noise, consequently the smoothing effect are decrease. But, the Sobel operator presented visually better enhancement of the ROI them all tested. Figure 1(C) shows the application of the Sobel filter image.



(A) (B) (C)

Figure 1. Step image processing: (A) Original RGB image, (B) grayscale image from HSI model, and (C) Sobel filter

To enhance image points, brightness, contrast, and gamma correction (BCG) were adjusted for the improve image display (Gonzalez; Woods, 2000), as well as to highlight on the ROI. The result of the rearrangement of the image with increased to 90% brightness and BCG values is presented in Figure 2(A) and (B).

The f(x, y) are binary values on image at pixel position (x,y), for a system Cartesian coordinate originated at the top left corner of the image, and b (x, y) are binary values sub-image, known like operator of the dilatation, based on choosing the parameter in sub-image to maximum value of (f + b) that result in an increase in region clearer and decrease or elimination in region dark. In other hand, erosion, it is based on the minimum value of (f - b), that result in a decrease in region clearer and increase region dark, so region before eliminated from dilation will not be more shown (Gonzalez and Wood 2000). The Figure 2 (C) and Figure 3(A) show the effects the image processing of the dilation and erosion, respectively. Figure 3 (B) show the result to find straight edge on image using the function from library Labview ’Find Straight Edge’.

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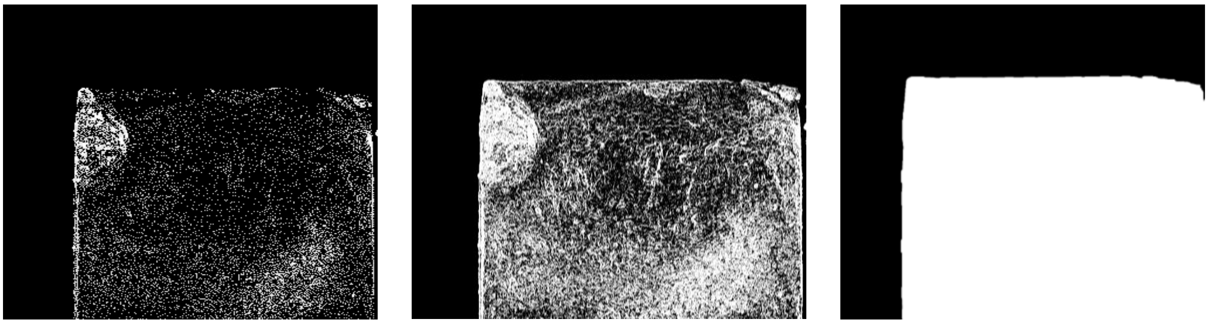


Figure 2. Step image processing: (A) image with increased to 90% brightness, (B) Brightness, contrast and gamma correction (BCG), and (C) Dilation Image

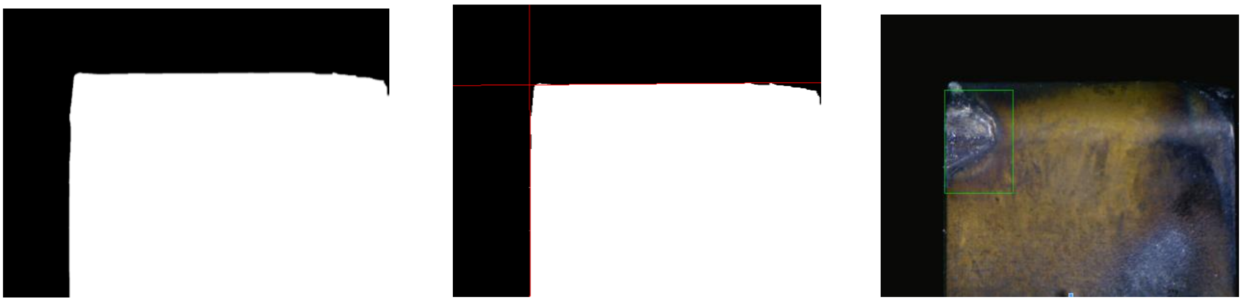


Figure 3. Step image processing: (A) Erosion Image, (B) Detection straight edge, and (C) Region of interest (ROI) to analysis damage and measure flank wear

After identified the edge image and based in ISO 3685 standard, that delimited the region where flank wear measure, a rectangle was defined as region of interest (ROI), Figure 7 (C).

2.2 Classifier between damage and flank wear

After setting the ROI, this step was discriminate flank wear and damage. When the ROI recognized as damage the cutting tool was discard. If not, the flank wear was measurement using next step.

The texture characteristic intuitively provides measurement of properties such as smoothness, roughness and uniformity surface of the image (Gonzalez and Woods, 2000). There are two ways to accomplish texture measures of the image, level histogram moments and analyzing the co-occurrence matrix. We opted for the use of the second way by the fact that load information of the relative position of pixels in relation to each other, considering not only the distribution of densities the method from the histogram, but also the positions of the pixels with values of equal or similar intensity.

Given the matrix C (normalized co-occurrence matrix), the texture of the ROI were calculated: Energy (position operator 45 and first amplitude, and number of gray levels reduced to 16; correlation (with the position of the operator 45 and the first amplitude and number of gray levels reduced to 16); inertia (using a position operator 90 and the first amplitude, and gray levels reduced to 32;and inertia (using an operator to position 0 ° to 1 range without reduction of gray levels).

According Theodoridis and Koutroumbas (2003) pattern recognition is the field of science which aims to object classification in a certain number of classes based on the analysis of its features. Duda et al. (2001) states that pattern recognition is aimed at building a more simple representation of a set of data through its outstanding features, allowing its partition into classe. In this context, the purpose of the classifier is to find an optimum solution which minimizes the probability of misclassification. Classifiers are surfaces (straight, curve or hyperplane) in n-dimensional space separating the classes of sets standards with similar characteristics. For this function, we used the Bayes decision function for the class of Gaussian standards (Johnson& Wichern, 1999).

Thus was used a Bayes classifier, where the parameters are the mean, covariance and priori probability of the classes. The probability of classifying an individual in a class j, P (wj | X) or Dj (X), when considering different covariances for each class, is estimated by quadratic discriminant function Eq.(4) :

$$D_j(X) = -\frac{1}{2}(X - \overline{X}_j)^T(\hat{\Sigma}_j)^{-1}(X - \overline{X}_j) - \frac{1}{2}\ln\left|\hat{\Sigma}_j\right| + \ln[P(w_j)] \tag{4}$$

Where: Dj (X) = discriminant function value for class wj of vector X; X = characteristic vector of on observation; $\bar{X}_j$ = mean characteristic vector of class j; $\widehat{\Sigma}_j$ = covariance matrix estimation of class j; $|\widehat{\Sigma}_j|$= determinant of covariance matrix estimation j; e P(wj) = a priori probability of class j.

It was considered a priori probabilities of 0.5 damage and 0.5 flank wear. For two classes defined previously in the image (damage and flank wear), the characteristic vector X representing an observation is classified into the jth class if $D_j = \max_{j=1\ldots k}[Dj(X)]$.

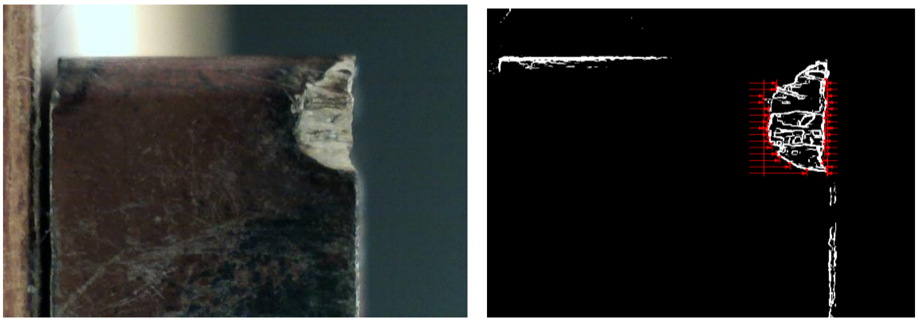
2.3 Measure flank wear

The flank wear width maximum (VB max.) and flank wear width average (VB) are values regulated by the ISO 3685 standard, which requires that the insert discard criterion is VB max. bigger than 0.6 mm or VB bigger than of 0.3 mm.

The edges and noise in the gray image affects to the high frequency contents of its Fourier Transform. Therefore, the resulting from the application of a low-pass filter is obtained in the field via frequency attenuation for a specific range of high frequency components in the transform of a given image (Gonzalez and Woods, 2000). Continuing the pre-processing, a low-pass filter was applied due to the features mentioned above. To mitigate the application of the low-pass filter about small noise and good edge, erosion operation technic was used.

Usually, segmentation technic is the first step in image analysis, aims to isolate the object of interest. In this step, also the Sobel filter was applied for segmenting the edge and BCG correction values were altered in this step also, thus the flank wear get enhance.

The final stage of the program consisted in measuring the VB max. and VB (Figure 4). For this task we used the function from Library LabView 'IMAQ Clamp Horizontal Max VI', which performs measurements in the horizontal direction from the vertical sides of ROI. This VI (Virtual Instrument) from LabView find edge along a set of parallel lines, and the edges are determined based on its contrast and inclination.



(A) (B)

Figure 4. Measuring of the flank wear width: (A) Original image and (B) measure flank wear width, VB max. and VB

The Figure 5 shows the step by step from read image, detection and eliminate damage until flank wear measure.

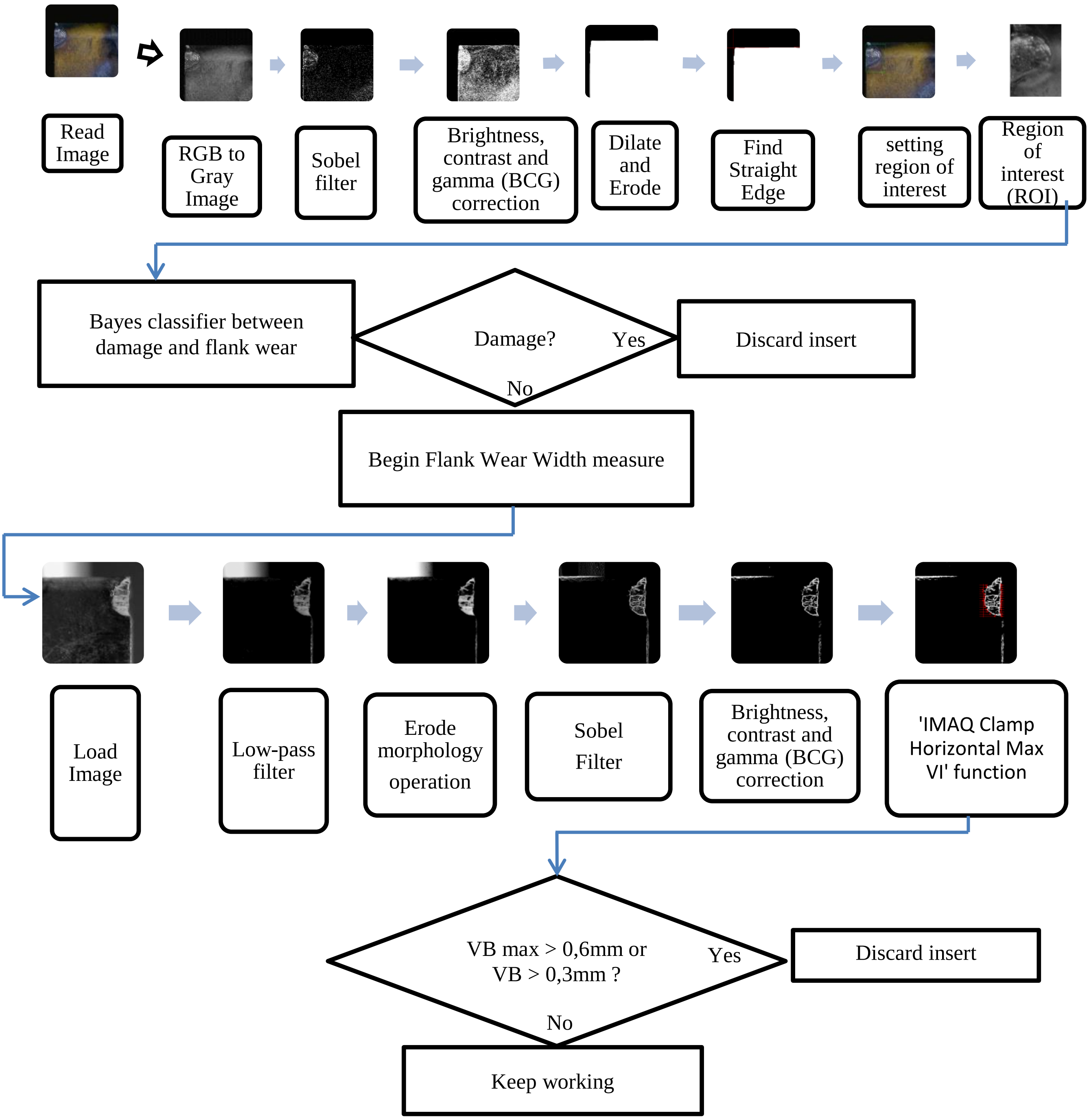


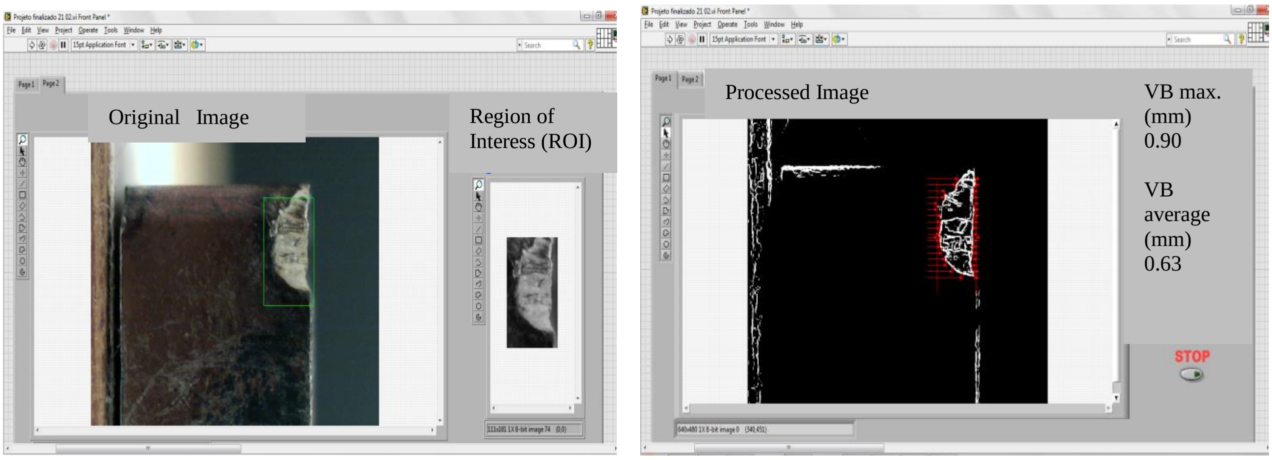
Figure 5. Flowchart for illustrate the procedure the image processing

The techniques most commonly used in performing accurate assessment of remote sensing data classification is the use of error matrix or confusion (Congalton, 1991). This matrix is a square array that consist in line and columns express the number of sample to a particular category relative to the current category. Normally, the columns represent the reference data while the lines represent the classification obtained from classifier function. Therefore, a confusion matrix was used to verify the effectiveness of the image classifier. To validate the VB measures, was calculated the relative and absolute error between the measured values obtained by the developed program and the manually measured values by Motic Images Plus 2.0 software.

In order to assess the statistic about classifier, since the overall error does not take into account the commission and errors of omission, Cohen (1960), cited by Rosenfield and Fitzpatrick-Lins (1986), developed a concordance coefficient named Kappa. Congalton and Mead (1983) defined that the Kappa statistic can be used to evaluate classifiers, because the data of the confusion matrix are discrete and multinormal distribution. According to the authors, this statistic is a measure of the real accuracy above of the randomly.

3. RESULTS AND DISCUSSION

The Labview platform allowed a user-friendly interface. Figure 6 (A) shows an example the interface the original image and after defined ROI. Figure 6 (B) shows the VB max and VB result.



(A) (B)

Figure 6. Interface of the program development in the Labview platform: (A) Original image and ROI (B) Flank wear result

Table 1 shows the confusion matrix and statistic Kappa of the classifier which distinguish between the flank wear and damage.

Table 1. Confusion matrix and statistic Kappa

Class	Flank wear	Damage	Total Line	User's Accuracy	Commission error
Flank wear	197	4	201	98,0%	2,0%
Damage	3	19	22	86,4%	13,6%
Total Column	200	23	223		
Producer's Accuracy	98,5%	82,6%	Accuracy overall = 96,9%		
Omission error	1,5%	17,4%	Kappa = 0,827 p-value < 0.0001		

The producer's accuracy refers of the samples that were not correctly classified and belonging to the category, being omitted for the correct category. Already the user's accuracy indicates the probability that a sample is actually classified that category. Table 2 shows the classification performance levels for the Kappa value obtained, generally accepted by the scientific community (Fonseca, 2002).

Table 2. Kappa Coefficient and performance classifier

Kappa Coefficient	Performance
< 0	Bad
$0 < k \leq 0.2$	Poor
$0,2 < k \leq 0.4$	Fair
$0.4 < k \leq 0.6$	Good
$0.6 < k \leq 0.8$	Very good
$0.8 < k \leq 1.0$	Excellent

According with the Table 1 and Table 2, the classifier performed excellent, showing thus acceptable for application in discriminate damage and flank wear in monitoring cutting tools in the machining process.

Table 3. Measuring in mm of the flank wear maximum (VB max.) the insert from UFU, Software and manually

Number insert/ Flank	UFU (1)	Software (2)	Manually (3)	Relative Error (2) –(1)	Absolute Error (2) – (1)	Absolute Error (2) – (3)
F1 - 1	0,7619	0,7009	0,7667	8,009%	- 0,0610	- 0,0658
F1 - 2	0,6562	0,6787	0,6556	3,430%	+ 0,0225	+ 0,0231
F1 - 3	0,6296	0,6009	0,6556	4,562%	- 0,0287	- 0,0547
F1 - 4	0,7407	0,7906	0,7778	6,743%	+ 0,0499	+ 0,0128
F1 - 5	0,6296	0,6003	0,6444	4,654%	- 0,0293	- 0,0441
F1 - 6	0,7143	0,6898	0,7000	3,434%	- 0,0245	- 0,0102
F1 - 7	0,8307	0,8898	0,8618	7,110%	+ 0,0591	+ 0,0280
F2 - 1	0,8193	0,8667	0,8833	5,781%	+ 0,0640	- 0,0166
F2 - 2	0,8616	0,8778	0,8571	1,878%	+ 0,0162	+ 0,0207
F2 - 3	0,8036	0,7778	0,8028	3,213%	- 0,0258	- 0,0250
F2 - 4	0,8140	0,8120	0,8118	0,2470%	+ 0,0020	+ 0,0002
Average error				4,46%	0,035	0,027
Minimum error				0,2470%	0,00	0,00
Maximum error				8,009%	0,06	0,07

Table 3 presents the measuring of the flank wear obtained by software, UFU and manually, well as the comparison each other. Thus, the maximum average relative error was 8.00 % and the maximum error was of the 0.07 mm. These errors of the flank wear are below of the magnitude of the decision for discard or not a insert, that is 0.3 mm.

4. CONCLUSION

The image classifier implemented achieved overall accuracy of the 96.9% and Kappa coefficient of the 0.827, this mean an excellent performance. The flank wear measurement has achieved 95.5% average accuracy. Thus, this good accuracy shows that the software and image acquire developed in LabView platform proved viable.

5. ACKNOWLEDGEMENTS

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