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CLASSIFICATION AND CORRELATION OF SURFACE ROUGHNESS IN METALLIC PARTS USING TEXTURE DESCRIPTORS

SUAREZ, S[ir]; ALEGRE, E[nrique]; BARREIRO, J[oaquin]; MORALA - ARGUELLO, P[atricia] & GONZALEZ - CASTRO, V[ictor]

Abstract: *In this paper we present a method to classify the surface roughness in metallic part after machining processes using an artificial vision system. Two texture analysis methods are used: Co-occurrence matrix (GLCM) and the energy of the texture obtained by Laws' method. These descriptors are classified with Lineal and Quadratic Discriminant Analysis (LDA and QDA) and Artificial Neural Networks (ANN.) The best results have been achieved using the Laws mask R5R5 (94.03%) and the combined correlation descriptor extracted from the GLCM (94.23%), both classified using Neural Networks. These results show the success of the method and the possibility to correlate these descriptors with the average roughness (Ra).*

Key words: *roughness, laws, co-occurrence matrix, surface texture*

1. INTRODUCTION

Quality control of metallic materials demands the correct assessment of some parameters, in order to make sure that those products fulfill the requirements. One of the main problems is to detect the defective products by means of the surface roughness. This value is usually assessed using traditional contact techniques, such as the perthometer, which have several drawbacks: they are slow and make several accuracy errors. Therefore, more adequate techniques are necessary to get a better quality control, such as methods based on image processing, such as texture analysis.

Texture analysis methods have already been used to detect defects in aluminium or steel parts, with the aim of classifying faults in surfaces after machining, like grinding or polishing. Zhang *et al.* show a method based on using some shape and statistical features (Zhang et al., 2006), extracted from the Gray Level Co-occurrence Matrix (GLCM) (Haralick, 1978), as well as the energy of the texture (Laws, 1980). This system can label all the predefined defects with an accuracy of about 82%, which is near the human experts' performance.

Illumination is one of the factors that may influence the classification. Different characteristics of the surface are highlighted depending on how the light comes into contact with it. There are some works that analyze the changes on the lighting inclination (Chantler et al., 2002), or stereo photometry techniques (Persons, 2006), where the shadows yielded by different lighting directions allow to compute the geometry of the object, obtaining a great reduction of misclassifications.

One of the main problems is to achieve a good correlation between the value of the roughness yielded by the perthometer and the value obtained using the artificial vision technique. Some researchers (Al-Kindi & Shirinzadeh, 2007), (Al-Kindi & Shirinzadeh, 2009) have developed a method – the intensity topographic compatibility (ITC) – which computes the value of the roughness parameters combining some statistical measures, such as the mean and the standard deviation. Image processing and classification is also used in (Alegre et al, 2008) to carry out the quality control of the surface in steel pieces, using first and second order statistical texture descriptors, dividing the roughness into three different classes – low, medium and high – and classifying them by means of the kNN method.

In this work two texture descriptors are used: the GLCM and Laws masks, extracted from images which have been obtained from turning parts. The main objectives are on one hand, to evaluate some classification methods as Discriminant Analysis (LDA and QDA) and Neural Networks (NN), and, on the other hand, assessing the descriptor which better correlates with the mean roughness value (Ra) yielded by the perthometer.

2. MATERIALS AND IMAGE ACQUISITION

2.1 Materials

In this study cilindral parts machining by a MUPEM CNC multi–turret parallel lathe —ICIAR/1/42 model— were used. They were turning from stocks of 20 mm of diameter. Cutting tools were coated carbide inserts TNMG 160408PM GC4035 from Sandvik with coolant CIMPERIAL C60. Parts were of AISI 6150 steel. The roughness parameter Ra was achieved by a perthometer HOMMEL TESTER T 4000 using a simple length of 0.8 mm, an evaluation length of 4 mm and a measurement length of 4.8 mm. Three measurements are made for each part, Ra is the arithmetic mean of them.

2.2 Acquisition and pre-processing

The images of parts were captured using an AVT Oscar F-810C camera. The part was positioned over a 'V'- shape support. The lighting system provided diffuse illumination in the camera axis and was composed by a FOSTEC regulated light source DCR RIII, and a NER SCDI-25-F0 diffuse illumination SCDI system was used to avoid shines. A Matrox Meteor II frame grabber card was used to digitize the images. The optic assembly was composed of an OPTEM industrial zoom 70XL, with an extension tube of 1X and 0.5X/0,75X/1.5X/2.0X OPTEM lens. A 2X magnification was used. As illumination angle was employed the angular one.

Eight images were captured for each part, obtaining a total of 3394 images, 2261 from class 1 with roughness lower than 6 µm and 1123 images from class2 with roughness higher than 6 µm. To avoid errors from illumination in the image edges, a central area of the original images between x1=0, y1=490, x2=3272, y2=2085 was extracted. Then its size was reduced five times by the algorithm of k nearest neighbours, obtaining a final image of 654x319 pixels and 256 levels of gray.

3. FEATURE EXTRACTION

3.1 Co-occurrence matrix

The co-occurrence matrix represents the joint probability that a pair of points in the image satisfies a certain condition of distance and orientation. Let C_d be the co-occurrence matrix, it is normalized using the equation 1

$$N_d(i,j) = \frac{C_d(i,j)}{\sum_i \sum_j C_d(i,j)} \quad (1)$$

The condition in this work is to make the points being adjacent at a distance 1, 2 or 3, and an orientation of 0º.

3.2 Laws method

Laws method (Laws, 1980) consists of applying convolutions with several filters to images, yielding such many ones as convolutions are carried out. Let I be the initial image and $g_i \ldots g_n$ a set of filters, a generic image resulted after the convolution is defined $J_n = I * g_n$. Let $F_k(i,j)$ be the result of applying the k-th mask on the pixel (i,j), then the energy of the image for the filter k is computed by using equation 2. Each of these filters highlights a feature of the texture, so the new images will have values directly related to them. In this work different convolutions have been assessed, and the best one has been the Ripples – R=[1 -4 6 -4 1] –. The mask that we have used – R5R5 – is defined to neighbouhoods of 5x5, and its weighted mean has been used as descriptor.

$$E_k(r,c) = \sum_{j=c-5}^{c+5} \sum_{i=r-5}^{r+5} |F_k(i,j)| \quad (2)$$

4. CLASSIFICATION ALGORITHMS

This work is focused on supervised learning algorithms, whose aim is to get a rule – extracted using some elements as a training set – which allows classifying a new element into one of the predefined classes. The assignment of unknown samples to their corresponding group by means of the knowledge of the Discriminant functions is the final aim of the discriminant analysis. The LDA looks for lineal functions which allow to differenciate the samples of a set into the groups defined by the dependent variable. The QDA is a generalization of LDA, and it is used when the populations have different matrices of covariance. A multilayer Perceptron has also been used to carry out the classification. This network has *N* layers. The neurons of each one are linked with the neurons of the adjacent layers by means of weighted connections.

5. RESULTS

The results show that the best descriptors are the features extracted from the GLCM Correlation (C), First information measure of correlation (F), Second information measure of correlation (S) and the combination of those three (CFS). According to Laws, the best mask is R5R5, from all the 25 convolutions. A 60% of the samples have been used for the training and the other 40% for the test. 904 images have low roughness – class 1 – and 452 have high roughness – class 2 –. The results of the classification carried out with LDA are shown in tab. 1. The lowest error rates are yielded by the CFS (6.63%) descriptor and the R5R5 mask (6.41%).

Classes	C	F	S	CFS	R5R5
Class 1	9.73	4.2	9.07	5.19	7.19
Class 2	9.95	14.15	8.62	9.51	4.86
Error	9.8	7.52	8.92	6.63	6.41

Tab. 1. Error rates of the classification with LDA

Classes	C	F	S	CFS	R5R5
Class 1	9.73	4.53	9.07	7.07	7.19
Class 2	9.95	11.94	9.95	8.84	4.86
Error	9.8	7.00	9.36	7.66	6.41

Tab. 2. Error rates of the classification with QDA

The results of the classification carried out by means of QDA are shown in tab. 2. The best error rate is still obtained with the R5R5 mask (6.41%). It is worth to highlight that the C descriptor yields a lower error rate (7 %).

Descriptor	Cycles	N	Class1	Class2	Error
C	600	5	3.80	18.49	8.70
F	700	5	4.24	12.30	6.93
S	600	5	3.98	14.35	7.44
CFS	700	5	3.24	10.83	5.77
R5R5	300	3	6.53	4.86	5.97

Tab. 3. Error rates of the classification with Neural Networks

In tab. 3 the error rates achieved with Neural Networks are shown. The overall error rate is lower for all descriptors, although the error rates of the clases are highly imbalanced (except for the CFS descriptor). The lowest error rate is achieved by the CFS (5.77%). These results show that the neural networks have better performance than discriminant analysis.

6. CONCLUSION

A method to get better quality control of metallic pieces after machining processes correlating the value of the roughness and texture descriptors is proposed in this paper. Two different texture descriptors were analyzed, obtaining better results using the Laws mask R5R5 when it is classified by the Discriminant Analysis, and with the CFS when using Neural Networks. The best performance has been obtained using Neural Networks. These results show the correlation extracted from the GLCM and the R5R5 mask as an alternative to compute the roughness value and get better quality control. The obtained results show that it is feasible to use texture descriptors to evaluate roughness of metallic parts in the context of product quality. Future works will analyze the performance of other texture descriptors

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