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SURFACE ROUGHNESS CLASSIFICATION IN METALLIC PARTS USING HARALICK DESCRIPTORS AND QUADRATIC DISCRIMINANT ANALYSIS

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Abstract: *An artificial vision system has been used to classify metallic work-parts in base of their surface roughness. Haralick features have been computed through the gray-level co-occurrence matrix (GLCM) to analyze the texture of the parts. Quadratic and Linear Discriminant Analysis (QDA and LDA) algorithms have been worked out to classify the descriptors. Results have proved the validity of this method to classify metallic parts in two classes achieving hit rates of 97,4% using QDA.*
Key words: *Roughness, Discriminant Analysis, Co-occurrence matrix, Haralick, Surface texture*

1. INTRODUCTION

Surface finish and surface texture has a great influence in order to define wear, lubrication, fatigue, resistance and external appearance of a work-piece. Therefore, surface roughness measurement represents an important factor in quality control tasks of manufacturing industry. Even though contact methods have traditionally been used to assess surface roughness, they present several disadvantages. Nowadays, computer vision is a more powerful tool to perform this task due to high accuracy and low cycle time.

A suitable illumination is one of the mayor aims in computer vision (Chantler et al., 2002). Al-Kindi et al. (Al-Kindi & Shirinzadeh, 2009; Al-Kindi & Shirinzadeh, 2007) described a method, named intensity-topography compatibility (ITC), which asserts that the light is reflected in a manner in all directions according to the surface topography. This fact leads to a linear compatibility relationship between the light irradiance intensity of each point and the surface topography. The value of the roughness parameters is calculated combining some statistical measures, such as the mean and the standard deviation.

(Suárez et al., 2009) worked out two textured analysis techniques, one based on the co-occurrence matrix (GLMC) and other grounded on Laws' method, reaching a success rate of 94.23% and 94.03% respectively. (Morala-Argüello et al., 2009a) compared five feature vectors based on moments to evaluate the superficial quality of machined parts achieving an error rate of 6.5% using Zernike descriptors with k-nn classification. Several authors have studied the surface roughness through a frequency domain instead of the usual spatial domain (Morala-Argüello et al., 2009b; Grzesik & Brol, 2009).

The main purpose of this paper is to evaluate the effectiveness of several Haralick descriptors, based on the co-occurrence matrix, in order to measure the surface roughness in metallic parts. Furthermore, this research assesses two Discriminant Analysis methods (LDA and QDA).

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

In this study, thirteen Haralick texture features have been used to calculate the surface roughness of metallic work-pieces. The basis for these features is the gray-level co-occurrence matrix (GLMC) that characterizes the relationship between the values of neighbouring pixels. A GLMC is a square matrix whose elements correspond to the relative frequency of occurrence for pairs of gray level values of pixels separated by a certain distance in a given direction. For a coarse texture these matrixes tend to have high values near the main diagonal, whereas for a fine texture the values are scattered (Guang-Hai & Jing-Yu, 2008).

Mathematically, a GLMC, C, is defined over an n x m image I, parameterized by an offset (Δx, Δy), as:

$$C_{\Delta x \Delta y}(i,j) = \sum_{p=1}^{n}\sum_{q=1}^{m}\begin{cases}1, if\ I(p,q)=i\ and\ I(p+\Delta x, q+\Delta y)=j\\ 0, otherwise\end{cases} \quad (1)$$

Two vectors have been assembled to carry out the measures from the thirteen Haralick features. Vector 1 was calculated with distance 1 and direction 0º in the GLMC, consequently, it is formed by 13 descriptors. Vector 2 was created with distances 1, 3 and 5 and direction 0º in the GLMC, thus it is formed by 39 descriptors.

4. CLASSIFICATION ALGORITHMS

Discriminant Analysis techniques, also known as supervised learning algorithms, were used to classify new parts into two classes: low roughness -class 1- or high roughness -class 2-. In particular, LDA and QDA were computed. LDA produces a linear decision boundary between both classes and the class covariance matrices are assumed to be equal. QDA works with quadratic boundaries and is only viable with a high ratio objects versus variables. This classifier is very similar to LDA; however, it takes into account the different variance of each class by using the sample variance–covariance matrix of each class separately to calculate the discriminant score between each sample and each class (Dixon et al., 2009).

5. RESULTS

C1=Test images class1; C2=Test images class2; WC1=Wrong classified images class1; WC2=Wrong classified images class2; %EC1=Error class1; %EC2=Error class2; %E=Error rate.

Statistic	C1	C2	WC1	WC2	%EC1	%EC2	%E
Vector1 (LDA)	904	453	28	30	3,1	6,6	4,30
Vector1 (QDA)	904	453	41	12	4,5	2,6	3,9
Vector2 (LDA)	904	453	22	21	2,4	4,6	3,2
Vector2 (QDA)	904	453	32	3	3,5	0,70	2,6

Tab. 1. LDA and QDA classification for vector 1 and 2

H.F.=Haralick Feature; Func.=Function; E=Energy; C=Contrast; CO=Correlation; V=Variance; MI=Inverse difference moment; SA=Sum average; SV=Sum variance; SE=Sum entropy; EN=Entropy; DV=Difference variance; DE=Difference entropy; FC=Measure of correlation 1; SC=Measure of correlation 2.

H. F.	SC	FC	CO	SE	MI	SV	SA
Func.	-0,731	0,721	0,669	-0,318	-0,198	0,179	0,173
H. F.	**C**	**EN**	**V**	**DV**	**DE**	**E**	
Func.	0,140	-0,119	0,113	-0,104	0,084	0,045	

Tab. 2. Structured matrix vector 1

Results carried out with vector 1 are shown in table 1. QDA achieved a lower error rate (3.9%) than LDA (4.30%). Table 1 proves that results slightly improve with LDA when using vector 2 (3.2%), however with regard to vector 1, they improve significantly when using QDA (2.6%). To sum up, the lowest error rate is yielded by vector 2 and QDA (2.6%). Performance is meaningfully higher than in the previous works (Al-Kindi & Shirinzadeh, 2007; Suárez et al., 2009; Morala-Argüello et al., 2009a).

Descriptors with a higher influence in the classification were determined according to the structured matrix for the vector 1 as it is shown in table 2. The most suitable ones for a correlation of surface roughness are: information measure of correlation 2 (SC) (73.1%), information measure of correlation 1(FC) (72.1%) and correlation (CO) (66.9%).

6. CONCLUSION

This research demonstrated the success of applying a computer vision approach to evaluate the surface roughness in metallic parts through GLCM, Haralick descriptors and Discriminant Analysis as an alternative to contact methods. The best results, improving the previous ones, were obtained using several distances of GMLC and QDA algorithm with 2.6% error rates. Future works will analyze the performance of other descriptors in the frequency domain based on the wavelet transform and Gabor Filters Banks.

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