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Metal surface quality assessment using 2D texture features

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***Abstract* – Quality assessment is an important step in production processes of metal parts. This step is required in order to check whether surface quality meets the requirements. Progress in the field of computing technologies and computer vision gives the possibility of surface quality assessment using industrial cameras and image processing methods. Authors of different papers proposed various texture feature algorithms which are suitable for different fields of images processing. In this research 27 texture features were calculated for surface images taken in the different lighting conditions. Correlation coefficients between these 2D texture features and 11 roughness 3D parameters were calculated. A strong correlation between 2D features and 3D parameters occurred for images captured under ring light conditions.**

I. INTRODUCTION

A surfaces quality control is an important step during the production process of metal parts. It is necessary in order to check whether surface quality meets the requirements. The quality control gives possibility to detect parts with certain defects and can help to increase outcome and reliability of good products.

A surface roughness assessment is one of the main ways to control surface quality. There are two main groups of roughness assessment methods: contact and contactless. Contactless methods have an advantage that a surface remains untouched after a measurement is performed. Nowadays optical industrial cameras are widely used in the contactless surface quality assessment. A measurement speed of such method is higher in compare with other surface assessment methods.

If surfaces of measured parts have a complex shape and lens of a camera has a narrow field of view, some regions of image can be out-of-focus. Such regions have less information about surface, because fewer details can be obtained from them. Trambitckii *et al.* used different texture feature to segment and remove such regions [1]. After these regions were removed, further surface quality analysis can be performed.

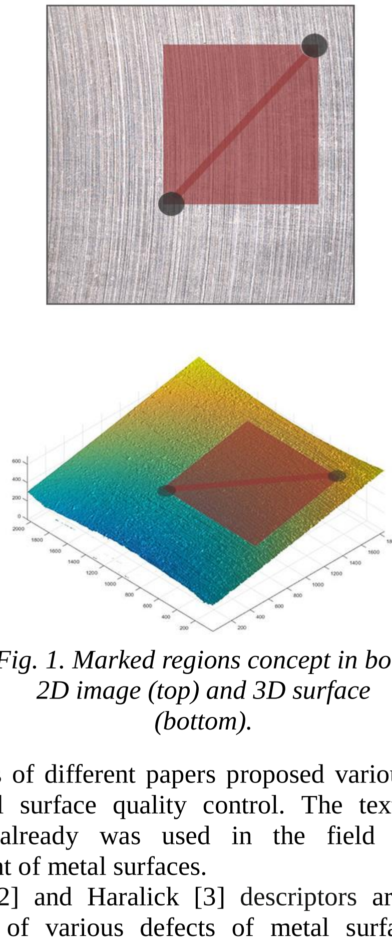

Fig. 1. Marked regions concept in both 2D image (top) and 3D surface (bottom).

Authors of different papers proposed various methods of optical surface quality control. The texture image analysis already was used in the field of quality assessment of metal surfaces.

Laws [2] and Haralick [3] descriptors are used for detection of various defects of metal surfaces. Laws developed an approach, which based on the calculating of texture energy. Convolution masks are used to filter the source image. Then texture energy descriptors are computed by using non-linear window operations on the filtered images. Finally all descriptors are combined to achieve rotation invariance of the resulting feature. To evaluate Haralick's descriptors, firstly the grey level co-occurrence matrix (GLCM) is calculated for an image. Values of GLCM are based on spatial location of pixels. Several GLMC can be created in different directions and different distances in relation to neighbourhood pixels. After that step Haralick descriptors (energy, contrast, correlation, etc.) for each GLCM are calculated. Alegre *et al.* used these both groups of descriptors as input vectors for k-nn classifier to define stainless steel surfaces in two classes based on their roughness quality [4]. Alves *et al.* took Haralick descriptors to describe roughness of the surface and use multilayer perceptron artificial neural network to classify these surfaces into three classes [5].

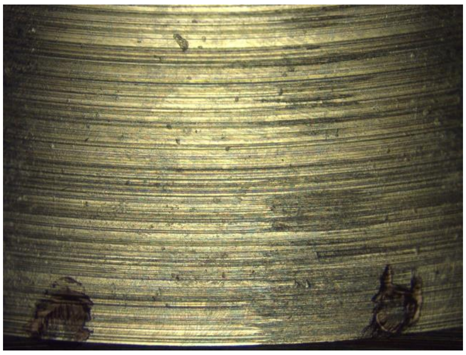

Fig. 2. Sample 2D image of metal surface.

Another way to calculate descriptors for classification is the wavelet transform. Alegre *et al.* [6] proposed to apply Haar wavelet transform to decomposed original surface images. As the next step Haralick features were calculated for these decompositions. This method shows reliable classification of surfaces based on their finish quality.

Another way of quality assessment can be based on the Fourier transform. Tsai *et al.* used two-dimensional Fourier transform to classify cast surfaces with different roughness in several classes. Naïve Bayes and neural network classifiers are implemented for this task [7].

In this paper the focus is on the surface quality control using various texture features. For this goal a correlation between different texture features and roughness parameters was calculated, which gives the possibility to find the most correlated pairs, suitable for contactless surface quality assessment. The algorithms were tested on surfaces produced by a milling and drilling operation.

II. DATA ACQUISITION

Metal parts with cone shaped surfaces were used in this research. Following the main concept of this experiment, processed test surfaces of metal parts were marked, as shown in fig. 1. That gives a possibility to find the same regions in the both 2D images and 3D surface data. In our research the size of the region of interest is around 1x1 mm^2. 3D roughness information of metal surfaces was obtained with the Alicona 3D Infinite Focus G4 measurement system. A lens with magnification of 20X was used. The lateral resolution (along X- and Y-axis) of the measurement system with 20X lens is 2.93 µm, the vertical resolution (along the Z-axis) is around 100 nm. 2D images were obtained with optical camera which built-in in the same system.

In optical measurements of metal surfaces lighting plays an important role. In this experiment several different lighting sources were used. The light through lens system of Alicona scanner was used, as well as a ring light in different modes. The main advantage of the ring light is rotation invariance of surface images shadows relatively to lighting source. A sample image of the surface with the ring light source, used in this research, is shown on fig. 2. The observed workpiece area was a counter sink. The cutting speed to produce these drill hole varied from 175 to 185 m/min.

III. 2D FEATURES EXTRACTION

27 different texture features maps were calculated for each image of the metal surfaces using MATLAB. The most correlated features are described in this chapter.

A. Thresholded gradient

Thresholded absolute gradient is calculated using the following equation [8]:

$$F_{GRAT} = \sum_{M}\sum_{N}\left|I(i, j+1) - I(i, j)\right| \quad (1)$$

while $\left|I(i, j+1) - I(i, j)\right| \geq \nu$,

where M and N are numbers of horizontal and vertical pixels of the image, $I(i,j)$ is the grey level intensity of pixel (i,j), and v is the gradient threshold.

B. Average central moment

Average central moment F_{ACM} is defined by [9]

$$F_{ACM} = \sum_{k=0}^{L-1}\left|k - \mu\right| \cdot h(k) \quad (2)$$

where L is the number of grey levels the image has, μ is an average value of grey levels of the image, and $h(k)$ is the value of a histogram h for the k-th grey level.

C. Spatial frequency

Frequencies for rows and columns are defined by [10]

$$RFreq = \sqrt{\frac{1}{M \cdot N}\sum_{i=1}^{M}\sum_{j=1}^{N}\left|I(i+1, j) - I(i, j)\right|^2} \quad (3)$$

and

$$CFreq = \sqrt{\frac{1}{M \cdot N} \sum_{i=1}^{M} \sum_{j=1}^{N} \left| I(i, j+1) - I(i, j) \right|^2} \quad (4)$$

Thus, spatial frequency is defined as

$$F_{SFRQ} = \sqrt{(RFreq)^2 + (CFreq)^2} \quad (5)$$

IV. 3D ROUGHNESS PARAMETERS

The surface quality can be estimated using roughness parameters established in international standards [11]. In this research the following ISO roughness parameters were used: S_a (arithmetical mean height of the surface), S_q (root mean square height of the surface), S_{sk} (surface skewness), S_{ku} (surface kurtosis), S_v (maximum height of valleys), S_p (maximum height of peaks), S_z (peak-peak), S_{10z} (10 point height), S_{dq} (root mean square gradient of the surface) and S_{dr} (developed area ratio). Along with the ISO parameters listed above another roughness parameter from other sources is used – S_{sc} (mean summit curvature) [12]. All these parameters were calculated for marked areas of the 3D surface, which correspond to the same areas of the 2D images.

V. CORRELATION EVALUATION

For this research 6 surfaces were taken and marked as shown on fig. 1. These marks can be visible both on images obtained with a 2D industrial camera and visible on a surfaces obtained with the Alicona system. That gives the opportunity to calculate different texture features and roughness parameters for the corresponding regions of a surface.

As the first step, regions of interest were set for every obtained 2D image and 3D surface. These regions of interest correspond to the marked areas of surfaces. Then marked areas were divided into subregions. Subregions for the 2D images and the 3D surfaces have different sizes because of their different original dimensions. The marked areas of the 2D images were divided into subregions of 35x35 pixels, marked areas of the 3D surfaces were divided into subregions of 140x140 points. These region sizes give the equal dimensions of resulting arrays, which is important for further correlation estimation.

In the next step, the texture features were calculated for each subregion of the 2D images. For every image every single texture feature resulting in an array of size corresponding to the number of subregions. Roughness parameters for the 3D surfaces were calculated in the same way. When texture features and roughness parameter arrays are calculated, correlation coefficients between every pair of the parameters were estimated.

Having two data arrays of similar sizes gives the possibility to find the correlation coefficient, which shows statistical relationships between these data values. If the coefficient is 0, it means that two values are linear independent. And the closer the coefficient is to -1 or 1, the stronger the correlation between these two values is. In other words, the closer the coefficient to these values, the stronger the linear dependency they have.

For correlation coefficient interpretation Brosius criteria [13] were used. These criteria are listed in table 1. This interpretation of the correlation coefficients gives an easier explanation whether values have weak or strong correlations.

Table 1. Correlation coefficients interpretation.

Absolute value of coefficients	Interpretation
0	no correlation
0 < r < 0,2	very weak
0,2 < r < 0,4	weak
0,4 < r < 0,6	medium
0,6 < r < 0,8	strong
0,8 < r < 1	very strong
1	perfect

VI. RESULTS

As the first step, a set of the texture features was tested against two sets of roughness parameters, calculated for raw surfaces and calculated for surfaces with removed curvature shape. The correlation for the second set was very weak, and in the next research only the raw surfaces data was used.

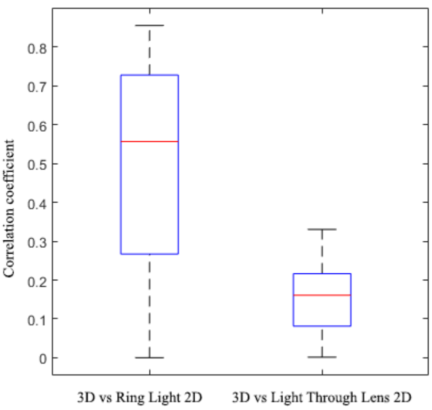

Fig. 3. Box plot for ring light and light through lens conditions.

Interesting results showed up with images under the ring light. The texture features calculated for these images showed strong correlations between the roughness parameters. The correlation for a ring light environment is stronger than for a light through lens conditions, see box plot in fig. 3.

The correlation coefficients between 27 texture features and 11 roughness parameters were calculated, resulting into an array of 297 pair-wise correlation coefficients. For all these coefficients absolute values were taken, as some of them have negative values. Then all pairs were sorted from the highest values of correlation coefficient to the lowest values. This information can be used to draw a plot, which shows a distribution of the correlation coefficients for all 297 pairs, see fig. 4. X-axis is the absolute correlation coefficient value. Y-axis represents an index number of pairs, sorted by the correlation coefficient value in descending order. The studies taken, showed that for our conditions the most correlated roughness parameters are S_a, S_q, S_v, S_p, S_{10z}, S_{sc}, S_{dq} and S_{dr}. The most correlated texture features are average central moment, thresholded gradient and spatial frequency.

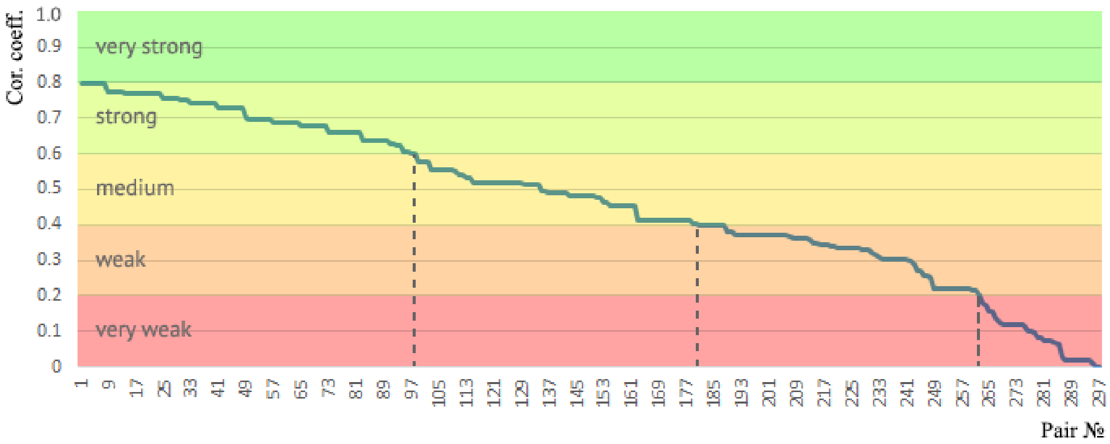

Fig. 4. Distribution of correlation coefficients.

VII. CONCLUSION

This research showed the successful results of using a computer vision approach for roughness assessment of metal surface with help of different texture features extracted from 2D images. Overall, 27 texture features were calculated for surface images taken in the different lighting environment. Correlation coefficients between these texture features and 11 roughness parameters were calculated. Strong correlations between features and parameters showed up for images with the ring light conditions. Future works will analyse surface images taken with other industrial cameras and different lenses. The results are indicating that surface defects, which are minted in a sufficient deviation of roughness parameters from its desired values, can be detected with fast operating low-cost 2D cameras using 2D texture analysis instead of using time-consuming and expensive 3D measurement devices.

VIII. ACKNOWLEDGEMENTS

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REFERENCES

[1] K.Trambitckii, K.Anding, G.Polte, D.Garten, “Elimination of out-of-focus regions for surface analysis in 2-d colour images”, Proc. of Ilmenau Scientific Colloquium, 2014, vol. 58,

[2] K.Laws, “Texture energy measures”, Image Understanding Workshop, DARPA, 1979.

[3] R.M.Haralick, K.Shanmugam, I.Dinstein, “Textural Features for Image Classification”, IEEE Trans. on Systems, Man and Cybernetics, vol. SMC-3, No. 6, 1973, pp. 610-621.

[4] E.Alegre, J.Barreiro, M.Castejón, S.Suarez, “Computer Vision and Classification Techniques on the Surface Finish Control in Machining Processes”, Lecture Notes in Computer Science, vol. 5112, pp. 1101-1110.

[5] M.L.Alves, E.Clua, F.R.Leta, “Evaluation of Surface Roughness Standards applying Haralick Parameters and Artificial Neural Networks”, IEEE Trans. on Systems, Signals and Image Processing, April 2012, pp. 452-455.

[6] P.Morala-Argueello, J.Barreiro, E.Alegre, S. Suarez, V.Gonzalez-Castro, “Qualitive surface roughness evaluation using Haralick features and wavelet transform”, Annals of DAAAM & Proceedings, January 2009, pp. 1241-1242.

[7] D.M.Tsai, C.F.Tseng, “Surface roughness classification for castings”, Pattern Recognition,

vol. 32, No. 3, March 1999, pp. 389–405.

[8] A.Santos, C.Ortiz De Solórzano, J.J.Vaquero, J.M.Peña, N.Malpica, F.Del Pozo, "Evaluation of autofocus functions in molecular cytogenetic analysis", Journal of Microscopy, December 1997, vol. 188, No. 3, pp. 264–272.

[9] M.V.Shirvaikar, "An Optimal Measure for Camera Focus and Exposure", Proc. of the Thirty-Sixth Southeastern Symposium on System Theory, 2004, pp. 472-475.

[10] A.M.Eskicioglu, P.S.Fisher, "Image Quality Measures and Their Performance", IEEE transactions on communications, 1995, vol. 43, No. 12.

[11] ISO 25178: Geometric Product Specifications (GPS) – Surface texture: areal.

[12] K.J.Stout, P.J.Sullivan, W.P.Dong, E.Mainsah, N.Luo, T.Mathia, H.Zahouani, "The development of methods for the characterization of roughness on three dimensions", Publication No. EUR 15178 EN of the Commission of the European Communities, Luxembourg, 1994.

[13] F.Brosius, "SPSS 8", International Thomson Publishing, 1998, p. 503.