Application of textural descriptors for the evaluation of surface roughness class in the machining of metals

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ABSTRACT

Measurement of surface roughness has been a matter of special interest in metal machining research during the last fifty years. Surface finish can be evaluated by means of some roughness parameters defined in international standards. These standards are oriented to tactile measuring devices that provide two–dimensional records of part profile. However, in the last decade, the improvement in computer vision and optics has encouraged many groups to research in the application of these technologies. Surface roughness evaluation is not an exception. The advantage of computer vision in this area is the characterization of wide areas of surface providing more information (3D information). In that context, this paper proposes a method based on computer vision to evaluate the superficial quality of machined parts. The method consists on the analysis of images of surface finish of machined parts by means of five feature vectors based on moments: Hu, Flusser, Taubin, Zernike and Legendre. Attending to these descriptors the images were classified into two classes: low roughness and high roughness, using k-nn neighbor's algorithm and neural networks. The moments used as descriptors in this paper show different behavior with regard to surface finish identification, concluding that Zernike and Legendre descriptors provide the best performance. An error rate of 6.5% was achieved using Zernike descriptors with k-nn classification.

KEYWORDS

Surface roughness, turning, moment descriptors, k-nn, neural network.

INTRODUCTION

Nowadays machining processes have two important goals: the optimization of machining parameters to get the required quality of products, and at the same time the maximization of production. This have made that in the last years the number of researches related to product quality control has increased exponentially, including those in the scope of surface finish control of machined parts. Surface finish can be estimated by means of some roughness parameters defined in international standards [1]. Development of these standards is basically oriented to tactile measuring devices that provide two–dimensional records of part profile. Nevertheless, surface measurement technologies have significantly evolved during last decades, from the first analogical contact devices to the current digital techniques [2]. According to Benardos and Vosniakos [3] the techniques for surface roughness measurement can be classified in: based on machining theory, experimental studies, approaches that use designed experiments, and artificial intelligence.
Among all these techniques, the one who offers most advantages and is easier to implement in the industrial environment is computer vision. The use of computer vision techniques for monitoring of machining operations has proved [4-6] an important reduction in the cycle time and the required resources.

Lu [7] presents a review of current research on the prediction of surface profile and roughness, based on the work of Benardos and Vosniakos [3]. Tarng and Lee [8] and Lee et al. [9] analyze the artificial vision and image analysis systems to quantify the roughness in different turning operations. The methods based on image analysis capture an image of the surface and analyze its pixels to obtain a diffuse light pattern. Later on, roughness parameters are calculated by means of statistical descriptors. One of the most used parameters is the standard deviation of gray levels. Kumar et al. [10] focus on milling, turning and molding processes. They make zoom over original images to obtain the Ga parameter (the image gray level average), finding a high correlation between the Ga parameter and the surface roughness. Al-Kindi ET al. [11] propose a method named intensity–topography compatibility (ITC), characterizing the image data by three components: lightning, reflectance and surface characteristics. They calculate the value of conventional roughness parameters combining statistical such as mean value and standard deviation. Lee et al. [4] developed a computer vision system that measures the roughness in turning processes automatically.

Kassim et al. [12] analyze machined parts and their correlation with tool wear using the column projection method and the method based on the connectivity oriented with fast Hough transform.

In this paper a new methodology is presented based on the use of textural descriptors to describe the surface condition. These descriptors are then used to classify the surface roughness in intervals.

MATERIALS AND METHODS

DESCRIPTION OF MACHINING TESTS

Test parts were of AISI 6150 steel with the chemical composition shown in table 1. A MUPEM CNC multi–turret parallel lathe —ICIAR/1/42 model— was used for the machining of parts. Cutting tools were coated carbide inserts TNMG 160408PM GC4035 from Sandvik. The covering quality of this insert was chosen in such a way that the tool wear rate were relatively high to accelerate the machining tests. Dimensions of stocks were 40 mm diameter and 60 mm length. The stocks were turned until 25 mm of diameter with 5 passes. Machining parameters were also chosen to accelerate the tool wear rate and, at the same time, to obtain a wide range of surface roughness values.

The Design of experiments (DOE) technique was used to plan the tests. The type of design of experiments most suitable was a 4^2 factorial design, so the number of resulting tests was 16. The factors were cutting speed and feed-rate. These factors were chosen since it is proved their significant influence on surface roughness. Cutting depth was kept constant since its effect over the surface finishing is scarce.

Table 2 shows the machining parameters for the tests. Several signals were monitorized during machining. In particular, vibrations and cutting forces were acquired using a Kistler triaxial accelerometer and a Kistler dynamometric plate, respectively. The surface roughness evaluation was performed for each part with a Hommel-Welke class 1 perthometer. The roughness parameter Ra was measured, obtaining, as expected, a wide range of values between 0.89µm and 21.29 µm. A total of 495 parts were machined and used for this research.

AISI	C	Mn	Si	Cr	Ni	Mo	V	Al
6150	0.48-0.55%	0.7-1%	0.15-0.4%	0.9-1.2%	-	-	0.1-0.2%	-

Table 1. Chemical composition of AISI 6150 steel

Test	Cutting speed [m/min]	Feed-rate [mm/rev]	Cutting depth [mm]	Range of roughness obtained (Ra) [µm]
A	280	0.15	1.5	1.6-8.49
B	280	0.25	1.5	2.99-14.04
C	350	0.4	1.5	5.89-11.32
D	350	0.15	1.5	1.24-2.12
E	320	0.4	1.5	5.86-7.02
F	250	0.15	1.5	0.94-4.48
G	280	0.55	1.5	11.23-21.29
H	250	0.25	1.5	2.79-4.64
I	320	0.15	1.5	0.86-2.61
J	250	0.55	1.5	3.62-6.84
K	320	0.55	1.5	10.66-18.19
L	320	0.25	1.5	2.18-2.8
M	350	0.55	1.5	12.62-17.74
N	250	0.55	1.5	11.4-13.46
O	350	0.25	1.5	2.39-3.13
P	280	0.4	1.5	5.72-10.05

Table 2. Machining parameters and range of roughness obtained in the machining tests.

IMAGE ACQUISITION

The images of parts were captured using an AVT Oscar F-810C camera (Figure 1). 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.

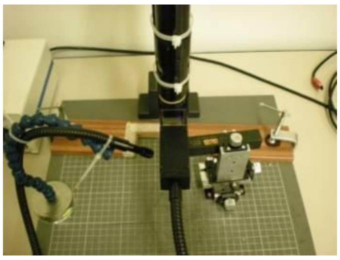


Figure 1. Acquisition system.

Eight images were captured for each part, obtaining a total of 3960 images. Each image was labeled with its correspondent Ra roughness value measured with the perthometer, calculated as the median of three repeated Ra measuring. Roughness values were in a wide range between 0.89 and 21.29 µm, depending on the machining parameters used.

The whole set of images was divided in two subsets, one containing 100 images of parts with acceptable values of roughness and another subset containing 100 images of parts with unacceptable values of roughness, that is, the two subsets constitutes the two ends of the spectrum of data. Figure 2 and Figure 3 show image samples for each of the subsets selected. The image resolution is 3272x1600 pixels.

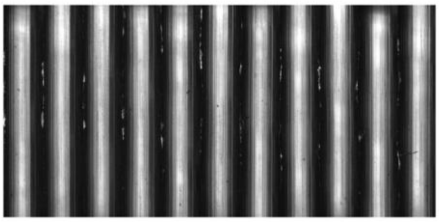


Figure 2. Original image with Ra 12.55 µm (high class).

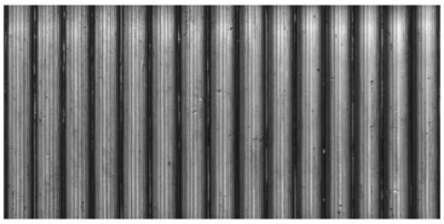


Figure 3. Original image with Ra 6.83 µm (low class).

IMAGE PROCESSING AND FEATURE EXTRACTION METHODS

A vertical Prewitt high pass filter was applied to the complete set of images in order to enhance contrast and make easier the description of roughness (see Figures 4 and 5). This filtering was applied because in previous works [13] it resulted useful for the interpretation process. However, in this work the result was not enough good as will be seen later.

Figure 4. Filtered image with high Ra.

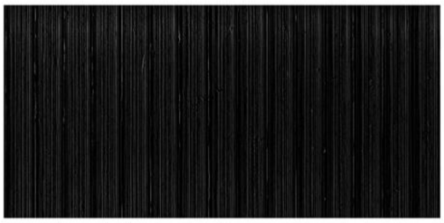


Figure 5. Filtered image with low Ra.

Several sets of descriptors based on moments were obtained both for the original and for the filtered images. Moments and functions of moments are invaluable tools in the literature for the measurement of the properties of a distribution. In the field of image analysis, their use as image descriptors was pioneered by Hu [14] when he applied the 2D geometric moments for characterizing the visual patterns in images.

Therefore, five different feature vectors were obtained for each image by computing the following texture descriptors based on moments: seven moments of Hu, six moments of Flusser, eight moments of Taubin, the moments of Zernike up to order 6 (16 features) and Legendre moments up to order 2 (9 features). For different images, the respective sets of moments are unique and this makes them particularly useful for the task of pattern recognition.

Moments of Hu. Hu derived seven invariant moments using nonlinear combinations of normalized central moments. In reference [14] can be found more detailed information about the mathematical expressions of Hu descriptors.

Moments of Flusser. Affine invariant moments of Flusser and Suk are derived from the algebraic invariant theory. They are invariant with regard to a general affine transformation. They use the central moments relative to several orders. The mathematical form for an affine transformation is indicated in reference [15]. Drawbacks of these moments are their sensibility to partial occlusions and the requirement to do a good segmentation previously.

Invariant moments of Taubin. Taubin and Cooper [14] proposed algebraic invariant moments to describe shape features. The matching of arbitrarily shaped regions is done by computing for each region a vector of centered moments. These vectors are viewpoint dependent, but the dependence on the viewpoint is algebraic and well known. They then compute invariant moments, i.e., algebraic functions of the moments invariant to Euclidean or affine transformations of the data set. The authors present a family of computationally efficient algorithms, based on matrix computations, for the evaluation of both Euclidean and affine algebraic invariant moments of data sets. The use of invariant moments greatly reduces the computation required for the matching, and hence initial object recognition.

Moments of Zernike. Although Zernike moments are computationally very complex compared with geometric and Legendre moments, in general, Zernike moments are better in terms of their ability to feature representation, rotation invariance, fast computation, multi-level representation patterns and low noise sensitivity. Zernike moments use a set of Zernike polynomials that is complete and orthonormal in the interior of the unit circle. The orthogonality property helps in achieving a near zero value of redundancy measure in a set of moments functions.

To calculate the Zernike moments, the image (or the region of interest) is first inscribed in the unit circle using polar coordinates, where the image mass center is the unit circle center and the image is included in it. Pixels out of the circle are not used for calculations. The coordinates are defined by means of the modulus of the vector from the origin to the coordinate point, r and θ, the angle between this vector and the X axis, positive in counterclockwise. Reference [17] contains more details about these descriptors.

Legendre moments. They are based on the polynomials of Legendre. The monomials basis functions increase very rapidly in range as the order increases, but they have the advantage that simple integer data representation may be used with discrete digitized imagery. The Legendre moments are defined in [17].

CLASSIFICATION METHODS

The former feature vectors were classified by means of two methods: k-nn and neural network. The neural network used was a multilayer Perceptron, with an output layer with one node for the classification into the low or acceptable roughness class and the high or unacceptable class. The number of nodes in the input layer was determined considering the dimension of input patterns in each case, which runs from six features corresponding to the Flusser descriptors until sixteen features corresponding to Zernike descriptors. The optimum number of nodes in the hidden layer and training cycles were selected empirically. The learning algorithm belongs to the group of 'backpropagation' algorithms, in particular the Levenberg-Marquadt optimized version.

The method of validation is a 'leave-one-out' cross-validation for k-nn classification and 'K-fold' cross-validation for neural network classification. The leave-one-out cross-validation method uses a single observation from the original sample as the validation data, and the rest of the observations as training data. This is repeated until each observation in the sample is used once as validation data.

In K-fold cross-validation, the original sample set is partitioned into K subsamples. A single subsample of the K subsamples is retained as the validation data for testing the model, and the remaining $K - 1$ subsamples are used as training data. The cross-validation process is then repeated K times, with each of the K subsamples used exactly once as the validation data. Then the K results from the folds can be averaged (or otherwise combined) to produce a single estimation. The advantage of this method over repeated random sub-sampling is that all observations are used for both training and validation, and each observation is used for validation exactly once. In this work 10-fold cross-validation is used.

Also, the effect of data normalization over the classification error was analyzed. The feature vector values were normalized, in such a way that a translation and a scaling were applied to each random sampling extracted from the training set. The translation of the group of vectors was applied from its own centroid to the origin of the space in order to achieve a medium value of cero. The scaling was done dividing each vector by the medium energy of the group, calculated as the root mean square. This operation leads to a standard deviation value of one.

RESULTS

K- NEAREST NEIGHBORS

Using k-nn classification method the best results were achieved with the orthogonal moments of Zernike and Legendre applied over the original images. Table 3 and 4 show the global error rate and the class error as a function of the value of k for these two descriptors. Ii is worth mentioning that the error rate in the class of higher roughness is considerably lower than in the class of lower roughness; this is due to the more clear contrast between peaks and valleys in the profile. The minimum global error is 6.5% with the orthogonal moments of Zernike.

The error rate obtained with the same analysis but using the filtered images was higher, concluding that, the Prewitt filtering is unnecessary and can be avoided, in contrast of expected. In the same way, no improvement was obtained in the classification when normalization of data is applied.

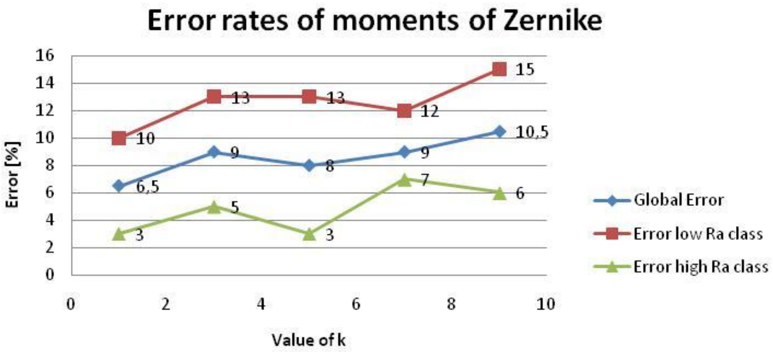


Figure 6. Error rates with moments of Zernike using k-nn classification

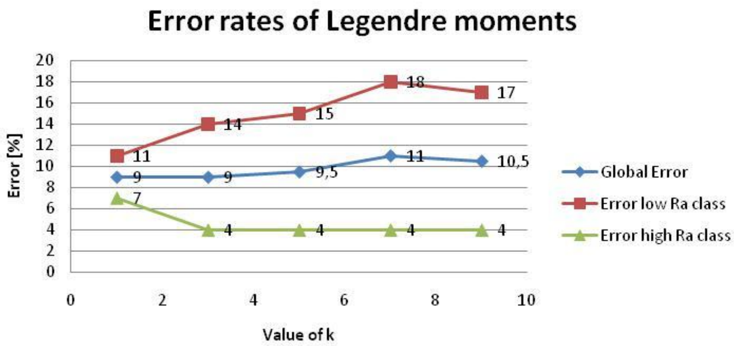
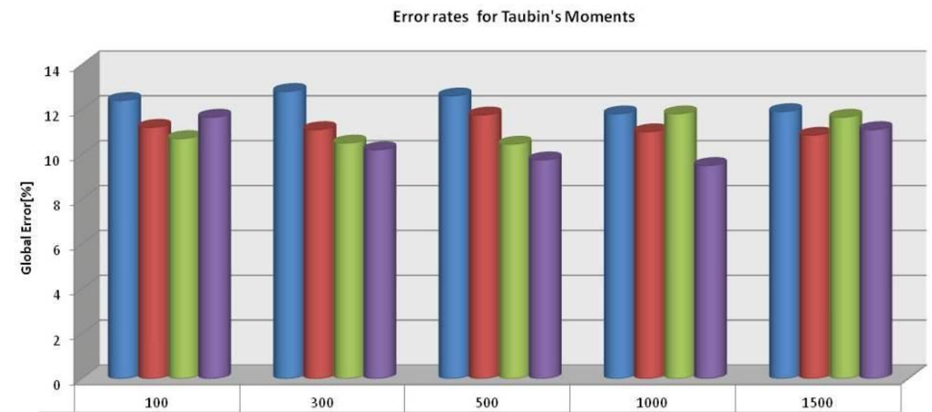


Figure 7. Error rates with moments of Legendre using k-nn classification

NEURAL NETWORK

When using neural networks as the classification method, the best results were achieved with the moments of Legendre and Taubin and the original images. Table 5 and 6 show the global error rates depending on the value of the number of nodes in the hidden layer. The lower error is 9.5%. As occurred in k-nn classification, the error rate with the filtered images and with data normalization are higher. Comparing these results with the previous ones, it can be seen that the errors obtained with knn-classification are lower than the ones obtained with neural networks.



Number of nodes	100	300	500	1000	1500
1	12,4	12,8	12,6	11,8	11,9
5	11,2	11,1	11,75	11	10,85
10	10,7	10,5	10,45	11,8	11,65
15	11,65	10,2	9,75	9,5	11,1

Number of cycles

Figure 8. Error rates with moments of Taubin using a neural network.

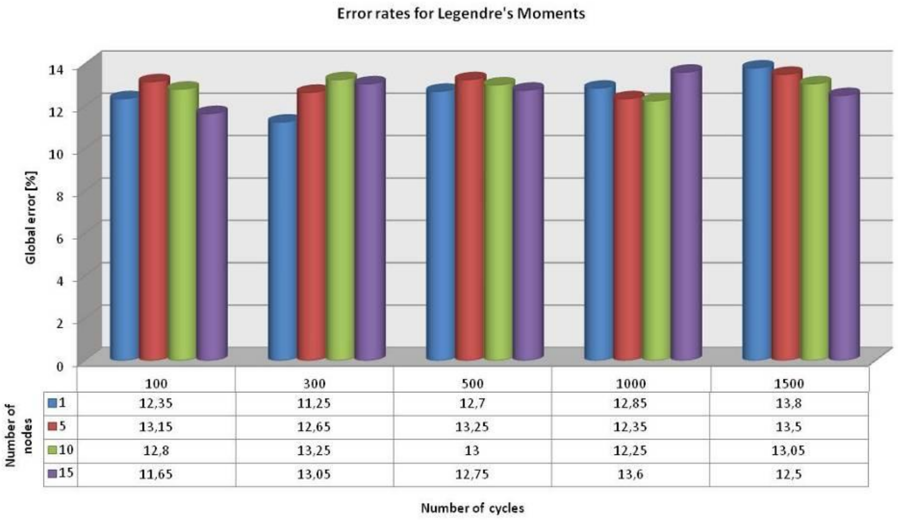


Figure 9. Error rates with moments of Legendre using a neural network.

CONCLUSIONS

A method to perform a surface finish control using a computer vision system is proposed, as an alternative to classical methods based on the use of perthometers. The advantage of the computer vision method is the possibility to do in-machine measuring and the chance to perform an exhaustive control of surface finishing, since the measuring is very less time consuming. In that context, the performance of five different sets of descriptors based in moments was analyzed. When using a K-nn classification method, only two of the descriptors analyzed show an acceptable behavior (error rates less than 10%), in particular the descriptors of Legendre (9% error rate) and Zernike (6.5% error rate). The rest of descriptors are not adequate to this problem, since the error rate is very high. However, when using a neural network classification method the only descriptor which offers acceptable results (below 10% error rate) is Taubin descriptors. These results mean that Hu moments and Flusser moments are no adequate in any case. Table 3 shows these data. In particular, Zernike moments with k-nn classification represent the best combination.

The results show that the use vision data with texture descriptors is a feasible method to evaluate the roughness of metallic parts in the context of product quality, although improvement should be done to decrease the error rate until 5% or less.

Descriptor	Error with k-nn[%]	Error with neural networks[%]
Moments of Hu	13	19.25
Moments of Flusser	40	30.75
Moments of Legendre	9	11.25
Moments of Taubin	42	9.5
Moments of Zernike	6.5	18.9

Table 3. Minimal errors with all descriptors

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