Determining Surface Roughness of Semifinished Products Using Computer Vision and Machine Learning

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ABSTRACT

In the production of components for various industries, including automotive, monitoring of surface roughness is one of the key quality control procedures since achieving appropriate surface quality is necessary for reliable functioning of the manufactured components. This study deals with the task of determining the surface roughness of semifinished products and proposes a computer-vision-based method for this purpose. To automate the design of the method, machine learning is used to induce suitable predictive models from the captured product images, and evolutionary computation to tune the computer vision algorithm parameters. The resulting method allows for accurate online determination of roughness quality classes and shows a potential for online prediction of roughness values.

1. INTRODUCTION

Quality control procedures in advanced manufacturing involve sophisticated techniques to meet the continuously increasing demands for product quality and reliability. Since humans are prone to failures in quality assessment, they are being replaced by autonomous quality control procedures. The automotive industry is one of the most advanced in this respect. Among the quality control measures, monitoring of surface roughness in the production of automotive components is crucial for achieving reliable functioning of the components throughout the product lifetime. There are several challenges associated with this task in production environments where the roughness measurement methods are required to be non-contact, autonomous and performing online.

This paper presents the development and evaluation of a computer-vision-based method for online surface roughness measurement in the production of commutators that are components of electric motors widely used in automotive industry. The method predicts the roughness based on the attributes of the captured commutator images. The design of the method was automated using machine learning and evolutionary computation.

The paper is organized as follows. Section 2 presents the problem of determining the roughness of a particular commutator surface. Section 3 describes the data preparation for offline development and evaluation of the proposed method. The methodology of machine learning and optimization used to design the method is explained in Section 4. Section 5 reports on the conducted experiments and obtained results. Finally, Section 6 concludes the paper with a summary of findings and a plan for further work.

2. PROBLEM DESCRIPTION

A commutator is a device mounted on the shaft of the rotor in a commutator electric motor. During the rotor rotation, the commutator sequentially reverses the current direction through the rotor winding and hence enables continuous commutation of the motor. The joint between the commutator and the rotor shaft is made by pushing the shaft into the commutator mounting hole. Usually, the manufacturer of electric motors specifies the maximum and minimum force to be applied during the mounting operation. If an excessive force is employed, there is a risk of damaging the commutator. On the contrary, if the applied force is too small, the joint cannot withstand the mechanical stress during the motor operation.

The force required to push the shaft into the commutator mounting hole depends on two dimensional characteristics of the hole – its diameter and roughness. Both characteristics result from the final treatment of the commutator mounting hole carried out in the turning process. Several methods are available for measuring the inner diameter of the holes. However, online measurement of surface roughness represents a major challenge.

The most frequently used method of surface roughness measuring is contact profilometry. It uses a specially designed measuring tip that slides over the surface and measures the displacement in the range of micrometers. However, this method has several drawbacks: it is very sensitive to vibrations, it is slow, and the measuring tip can cause additional scratches on the measured surface. Consequently, contact profilometry is not suitable for online surface roughness measurements. As an alternative, optical non-contact methods were developed, e.g., optical profilometry, scanning electron microscopy, atomic force microscopy etc. Unfortunately, none of them is suitable for online roughness measurement, since they are all sensitive to vibrations and, in addition, special samples have to be prepared for these methods to be applied.

Computer vision offers new possibilities in non-contact roughness measurement. For example, based on surface images captured by a CCD camera, calculation of a feature called the optical surface roughness parameter, G_a, was proposed and shown that it compares well wih the traditionally used average surface roughness, R_a, [2]. A machine vision system for online measurement of surface roughness of machined components was developed that relies on an artificial neural network model for predicting optical roughness values from image features [3]. It was also demonstrated that it is possible to measure surface roughness in three dimensions by combining a light sectioning microscope and a computer vision system [1].

In the literature, various parameters are considered in defining the measure of surface roughness [4]. They can be categorized into amplitude parameters, spacing parameters, and hybrid parameters. In our case, the commutator producer uses the parameter R_z which takes into account the difference between the maximum peak height and the maximum valley depth from a profile in the sampling length.

This research deals with the problem of determining the R_z parameter value and proposes an autonomous computer-vision-based method for this purpose. In addition, to automate the design of this method, machine learning and evolutionary computation are used. The resulting methodology is aimed at accurate online determination of the commutator mounting hole roughness on a commutator production line and is also applicable to other use cases requiring online surface roughness measurements.

3. DATA PREPARATION

The initial phase in designing a method for online surface roughness measurement was data preparation. It consisted of capturing the images of the commutator mounting hole surfaces, image preprocessing, and extracting attributes from the preprocessed images.

For the purpose of this study, 300 comutators were made available and the images of their mounting hole surfaces were taken in 8-bit grayscale with the resolution of 2592×1944 pixels. In addition, to obtain the reference values of their roughness for the purpose of machine learning, the samples were measured by a contact profilometer. To reduce noise in the obtained measurement data, each sample was measured three times and the average was then taken as a reference roughness value. Note that commutators with the roughness parameter value $R_z \leq 16$ µm are considered acceptable, while the ones with $R_z > 16$ µm unacceptable. The distribution of test images among the quality classes is shown in Table 1.

Table 1: Distribution of test images

Class	Number of images
Acceptable	159
Unacceptable	141

To preprocess the images and extract the attribute values from the preprocessed images, a dedicated computer vision algorithm involving a sequence of operators was implemented in the LabView programing environment [6]. Both the operators and the sequence of their deployment were determined manually, based on the experience from developing similar computer vision applications.

Image preprocessing is aimed at extracting the regions where surface roughness is to be measured. It comprises several steps as shown in Figure 1. It starts with an original grayscale image and applies a manually set threshold to it. The resulting binary image is then used to calculate the image centroid based on the pixel intensity. Since the mounting hole area always contains the highest proportion of high-intensity pixels, the calculated centroid is always positioned at about the same location of the mounting hole, regardless of its position in the image. In the next step, the coordinate system is assigned to the location of the calculated centroid. The coordinate system is used to precisely position the image mask for extracting an adequate region of interest (ROI) from the image. Finally, the image extraction mask is applied and part of the image inside the ROI is extracted. The result of this preprocessing is a cropped greyscale image of 700×300 pixels.

The attribute extraction procedure returns the values of 28 attributes describing the properties of the captured surface image, such as the grayscale value of pixels along the line profile in the image, the highest grayscale pixel value in the image, the lowest grayscale pixel value in the image, the distance in pixels between the stripes in the image, fast Fourier transform (FFT) values, etc. All extracted attribute values are numerical. The sequence of steps in the attribute extraction procedure is shown in Figure 2.

First, the fast Fourier transform (FFT) is applied to the image to eliminate the noise that results from inhomogeneities in the material. Based on the FFT results, certain proportion of high frequencies is rejected, thus removing noise from the image. However, despite the FFT frequency truncation, some noise may still be present. To further eliminate it, the median filter is activated next. This filter makes it possible to apply various structure elements in the image. As a result, in the longitudinal direction, where roughness is to be measured, details are preserved, while transversely they are filtered. The surface roughness in the image is thus emphasized. Afterwards, the surface line profile is measured and certain attributes are extracted from the grayscale image. To obtain additional attributes, the Niblack binarization algorithm [5] is applied. It returns a binary image with surface roughness represented by black and white stripes. Image processing with the Niblack algorithm may result in pixel clusters in the binary image. To eliminate these clusters, the particle filter operator is used. Next, morphology functions are applied to the binary image to equalize and straighten the edges of the stripes in the image. Finally, the attributes of the binary image are extracted and a file with all attribute values is generated.

4. MACHINE LEARNING AND OPTIMIZATION METHODOLOGY

The key phase in designing a method for surface roughness determination was machine learning of predictive models from the extracted attributes and the reference roughness values. For this purpose the open-source data mining environment Weka [9] was used. Two types of prediction were considered:

- classification, where the task is to label the surface roughness of a product as either *acceptable* or *unacceptable*,
- regression, where the task is to predict the value of the roughness parameter R_z for each product.

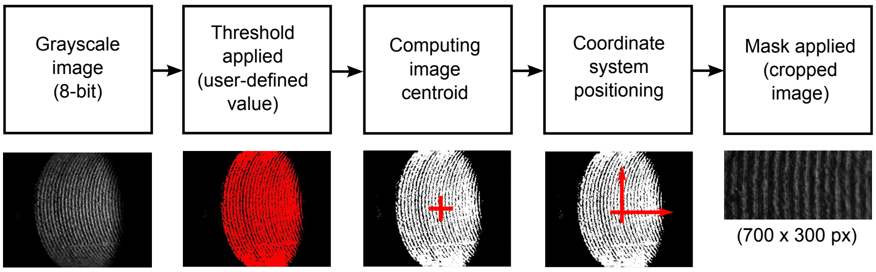

Figure 1: Preprocessing of the captured images

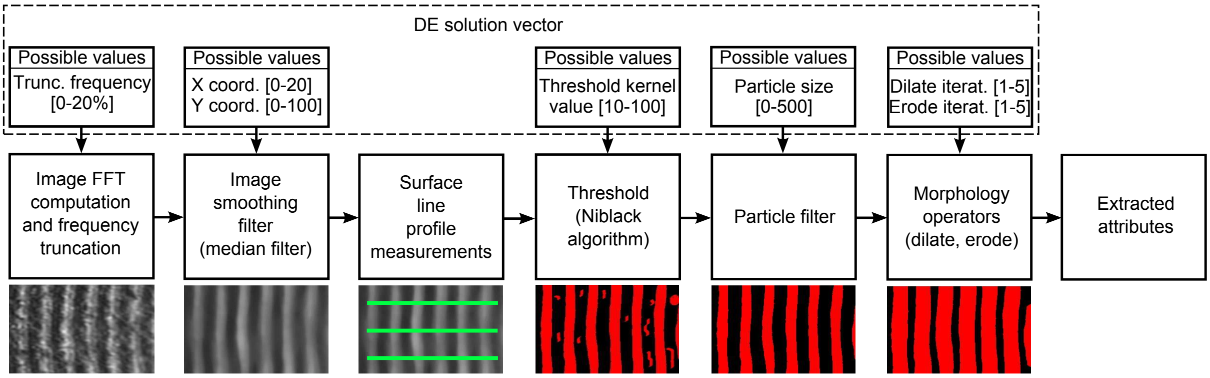

Figure 2: The attribute extraction procedure

For the classification task the Weka implementation of the C4.5 algorithm [7] for building decision trees from data, called J48, was used. This approach was selected since decision trees are simple to implement and easy to interpret. The J48 involves several algorithm parameters that influence the performance and complexity of the induced model. However, in this study we focused on tuning the computer vision algorithm parameters, while machine learning with J48 was carried out using its default parameters settings. The goal of tuning the computer vision algorithm parameters was to maximize the classification accuracy of the models induced from the image attributes. The classification accuracy was estimated through 10-fold cross-validation.

The regression task of predicting the value of the roughness parameter $R_z$was approached using the M5P algorithm for regression tree induction available in Weka. The leaves of regression trees produced by M5P contain linear models predicting the target variable value (R_z). Like J48, M5P includes several algorithm parameters too. For the same reasons as in the classification task, these parameters were set to their default values. Here, the objective of tuning the computer vision algorithm parameters was to minimize the Root Relative Squared Error (RRSE). The performance of the regression models was also validated with 10-fold cross-validation.

The methodology used for induction of predictive models and optimization of the computer vision algorithm parameters is shown in Figure 3. The optimization algorithm used in this methodology was Differential Evolution (DE) [8]. Solutions explored in the optimizaion process were vectors of parameters of the computer vision operators. The structure of a DE solution vector with the computer vision parameters subject to optimization is illustrated in Figure 2. After a solution is created, the computer vision algorithm, using

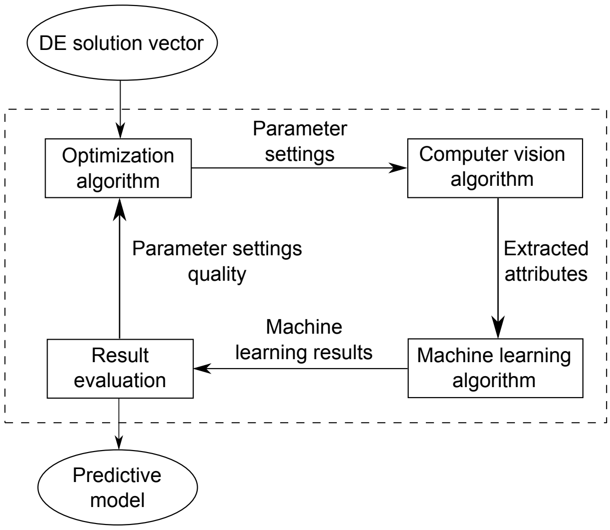

Figure 3: A schematic view of the methodology used for induction of predictive models and optimization of the computer vision algorithm parameters

the parameter values from the solution vector, preprocesses the input images and extracts the selected attributes. Next, the machine learning algorithm induces a predictive model from the attribute descriptions of the images and evaluates its performance. The evaluation result is passed back to the optimization algorithm, which generates a new solution. This iterative optimization procedure repeats until the stopping criterion specified in terms of the number of evaluated solutions is met.

5. EXPERIMENTS AND RESULTS

The presented methodology was evaluated on the acquired and preprocessed images in designing both the classification and the regression method of determining the surface roughness. We first focused on the classification task. The population size in the DE optimization algorithm was set to 10 and the algorithm was executed for 100 generations. Several runs were performed and the algorithm was consistently able to find decision trees with the classification accuracy of 100% in very few examined generations (no more than 10). This clearly indicates that the learning domain is not very complex. An additional analysis of the reference roughness values showed that they were dispersed very non-uniformly in that a roughness value was either well bellow or above the class discriminating value of R_z = 16 μm (see Figure 4). Moreover, a closer look at the induced decision trees revealed that in most cases a single attribute test was sufficient for accurate classification. Several attributes were identified as informative enough for this purpose: the FFT index value indicating the frequency of the stripes in the binary image, the average width of the stripes in the binary image, and the highest grayscale pixel value from the valley minima.

Next, the regression task was pursued. The population size and the number of generations in the DE algorithm were set to the same values as for the classification task, resulting in 1000 examined candidate solutions. In multiple runs of the optimization algorithm the RRSE value of the resulting regression trees in predicting the R_z roughness parameter value was found to be around 22% and its deviation between individual runs negligible. The calculated mean absolute error of these models was 0.75 μm, which is quite an encouraging result. The typical size of the regression trees was five nodes, i.e., two internal nodes with attribute tests and three leaves containing linear models for determining the surface roughness. The highest grayscale pixel value from valleys minima was found to be the most informative attribute in the trees. The surface roughness values predicted by a derived regression tree are compared to the measured reference values in Figure 4.

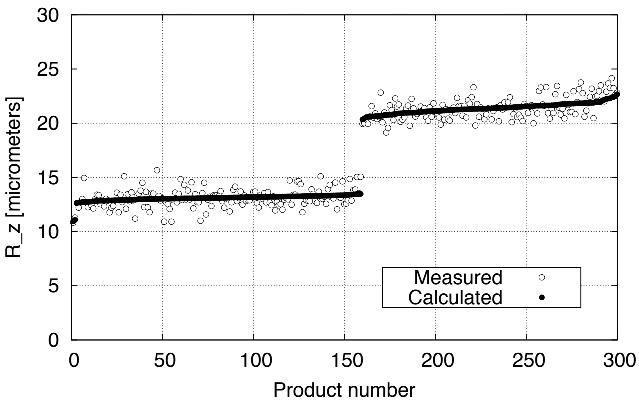

Figure 4: Comparison of measured and calculated roughness values

These results indicate that the proposed machine-learning creation of models for predicting surface roughness from the image attributes is a viable approach to the design of a computer-vision-based roughness measurement method. Under laboratory conditions, the study demonstrates that classification of surfaces into roughness quality classes can be performed accurately, while predicting the R_z value is not yet at this level, in our view mainly because of the very limited amount of product samples available for learning.

6. CONCLUSIONS

We have presented the development and experimental evaluation of a computer-vision-based method for determining the roughness of machined surfaces of semifinished products for automotive industry. Offline design of the method consists of building a predictive model from the attribute descriptions of the product images and optimization of the attribute extraction procedure. Once designed the model can be ported to an appropriate smart camera system to perform online roughness measurements within a quality control procedure on a production line.

The conducted laboratory evaluation confirms the suitability of the approach and, at the same time, indicates the need for refining the regression model for determining the roughness value. For this reason, further work will concentrate on deriving the model from a larger, systematically gathered and more representative set of samples. We expect the resulting model to be accurate and capable of detecting trends in the product roughness value that will be informative for taking appropriate process control measures. In addition, the optimization of the method will be extended to involve not only the parameters of the attribute extraction procedure but also the machine learning algorithm settings. Finally, online deployment and evaluation of the developed method in the production environment will be carried out.

7. ACKNOWLEDGMENTS

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8. REFERENCES

[1] O. B. Abouelatta. 3D surface roughness measurement using a light sectioning vision system. In *Proceedings of the World Congress on Engineering, WCE 2010, London, U.K.*, volume 1, pages 698–703, 2010.

[2] B. Dhanasekar and B. Ramamoorthy. Evaluation of surface roughness using a image processing and machine vision system. *MAPAN – Journal of Metrology Society of India*, 21(1):9–15, 2006.

[3] D. A. Fadare and A. O. Oni. Development and application of a machine vision system for measurement of surface roughness. *ARPN Journal of Engineering and Applied Sciences*, 4(5):30–37, 2009.

[4] E. Gadelmawla, M. Koura, T. Maksoud, I. Elewa, and H. Soliman. Roughness parameters. *Journal of Materials Processing Technology*, 123(1):133–145, 2002.

[5] J. He, Q. D. M. Do, A. C. Downton, and J. H. Kim. A comparison of binarization methods for historical archive documents. In *Proceedings of the Eighth International Conference on Document Analysis and Recognition, ICDAR '05*, volume 1, pages 538–542, 2005.

[6] T. Klinger. *Image Processing with LabVIEW and IMAQ Vision*. Prentice Hall Professional, 2003.

[7] R. J. Quinlan. *C4. 5: Programming for Machine Learning*. Morgan Kauffmann, 1993.

[8] R. Storn and K. Price. Differential evolution – A simple and efficient heuristic for global optimization over continuous spaces. *Journal of Global Optimization*, 11(4):341–359, 1997.

[9] I. H. Witten and E. Frank. *Data Mining: Practical Machine Learning Tools and Techniques*. Morgan Kaufmann, 2005.