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SURFACE TEXTURE FUNCTIONALITY CHARACTERISATION

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ABSTRACT
The observation of the surface texture is often subjected to ad hoc illumination conditions and subjective evaluation. In this paper it is reported on the experimental set-up for the surface texture characterisation with which it is possible to overcome this situation.
Keywords: surfaces, texture, image processing, inductive machine learning

1. INTRODUCTION
In the domain of micro-manufacturing, quality control tasks are regularly implemented between production phases and especially before packaging, since more than half of the price is in the cost of final packaging as it is example in the MEMS and semiconductor production. Similar is the situation in the tool manufacturing where final operation is surface finishing which is very labour intensive and contributes up to 5% to the total price of the tool. In order to find a way to fast and qualitative method of surface finish characterisation in this paper we report on a surface texture characterisation device, based on the computer controlled illumination, image acquisition and digital image processing.
Surface texture is an important surface attribute, since regardless of the manufacturing process, the machined surface retain the irregularities, patterns and textures that are characteristic of the process. The importance of surface texture is twofold. It is as important from the functional as from the aesthetically point of view. It would be of great benefit if the texture pattern can be monitored and evaluated in-process in order to adjust machining parameters.
Wirtz derived a systematic approach of surface texture description, based on geometrical relations between feed and work direction [1]. In his work also the influence of disturbances such as vibrations or material inhomogenities on a surface texture and surface functional behaviour were discussed. With the advent of digital image processing it became possible to quantitatively evaluate surface textures from this point of view, but the complexity of the task still hinders the realisation. In the contrast with this early work now many papers are published in the domain of texture characterisation, most of them originating from the computer science, but only a part of them discuss manufactured components and actual texture measurements.
The insights into the surface generation process during machining are given by the unit event approach as researched by Whitehouse [2]. In his work the relationship between the micro-topography of a unit event and macroscopic surface characteristics such as surface roughness is formalised. Regarding functional behaviour, he discussed surface gloss of optical elements extensively [3]. The unite event approach has been used also to simulate surface generation in non-conventional machining processes such as electro discharge machining [4] and abrasive waterjet machining [5].
The relationship between machining parameters, signals acquired during machining, surface topography characteristics, and surface functional behaviour is a very complex function, difficult to obtain. Junkar et al. [6] used inductive machine learning to derive a formalised description of selected machining process performance. It is a hypothesis, to be confirmed in the continuation of the present

experimental paper, that also in the case of surface texture functionality characterisation plausible knowledge database entries can be obtained by inductive machine learning.

2. EXPERIMENTAL METHODOLOGY

Experimental set-up was built consisting of hemisphere with mounted computer controlled light emitting diodes, illuminating the measured surface with angle ϕ selective from 12.8^o to 77.4^o in regular steps as shown on the Figure 1. Measured surface - specimen was mounted on a rotating support directly driven by a computer controlled stepper motor. The minimal available rotation step is 1.8^o. CCD camera was positioned coaxially with the axis of the stepper motor and the aperture in the hemisphere.

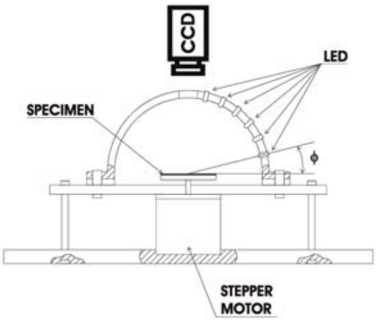

Figure 1. Experimental setup consists of semi-sphere with mounted light emitting diodes. Specimen is illuminated by the LED light with the angle of incidence ϕ.

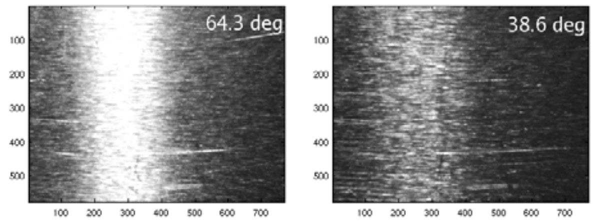

Figure 2. Images of a ground surface, acquired with different LED turned on.

A computer control program was written in Matlab program to control the image acquisition procedure. For each rotation angle six images were stored each with different LED turned on. At the present time turned, milled and grinded steel samples were used. On the Figure 2 two images of a grinded surface roughness normal with average surface roughness Ra=1.6 μm. The images were acquired with 5th and 3rd LED turned on which corresponds to impact angles ϕ = 64.3^o and 38.6^o respectively.

3. SURFACE ROUGHNESS ATTRIBUTES - MACHINE LEARNING DOMAIN

3.1. Expert system

Arbitrary process can be treated deterministically, statistically or by using the methods of artificial intelligence. Deterministic approach can be used if the dependencies between input and output quantities are known and the system disturbances are significantly small. Statistical approach takes into account the results of many repetitions for example measurements and determines relations using statistical methods.

Methods of the artificial intelligence describe the problem domain different, mostly by some symbolic description language. Among the methods which are mostly used are: expert systems, neural networks, or genetic algorithms.

In the case of expert systems knowledge is usually presented in the form of the set of rules in the form *{if condition P, than conclusion C}*. It turns out that are if-then rules are the most transparent form of knowledge presentation and it is easy to add new rules independently from the rest of the rules in the set.

Expert system is built for the specific problem domain and consists of three parts: knowledge database, inference mechanism and user interface. In the knowledge base, the knowledge needed to make decisions on the problems from the problem domain is stored. Inference mechanism which can actively use the knowledge from the knowledge database and the user interface consist the expert system shell which is now commercially available software. In the prime concern of the problem domain expert is therefore how to provide the knowledge to fill up the knowledge base.

3.2. Inductive machine learning

Knowledge is multilayered by its nature. It is not necessary that two persons executing equal set of tasks have equal amount of knowledge. The first one, e.g. operator for example, has maybe adapted to the work without understanding the background, but the other one, expert, has advanced theoretical domain knowledge. We are interested in their capability to document and transfer their knowledge. Operators' knowledge is on the level of craftsmanship. During the adaptation period he gradually learned to perform his tasks. He has difficulties to transfer the knowledge in the form of written advice, but can easily classify the process results in a few classes of quality. If the observed process is in the same time monitored by sampling, the gathered signals together with the expert classification form a learning set of pairs: {quantitative-process-attributes; class}.

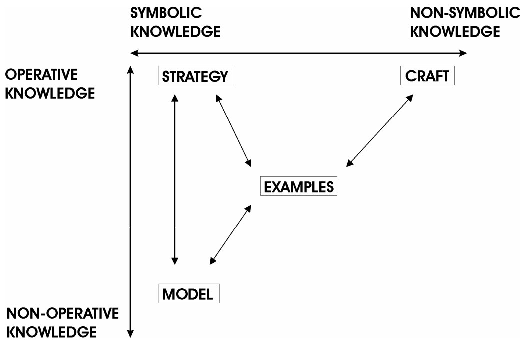

Figure 4. Forms of knowledge positioned with respect how operative it is and the level of symbolic language [7].

From the learning set a quantitative concept in the form of decision tree or if-then rules can be derived by the inductive machine learning software.

In the Figure 4 relations between different forms of knowledge is schematically presented. We see that craftsman’s knowledge is highly operative, but can't be disseminated in the form of symbolic language [7]. The surface measuring system, described in this paper acquires vast amount of digital images, which have to be processed in order that surface texture attributes can be extracted from. Resulting surface attributes are still far away from craftsmanship experience; therefore before useful concepts can be derived the inductive machine learning should be used. In our work the inductive machine learning tool Assistant professional [8] software tools were used.

4. SURFACE ROUGHNESS ATTRIBUTES

The most important step towards the acquisition of the surface texture related knowledge is to extract the surface attributes common to the specific image features. An image feature is a distinguishing primitive characteristic or attribute of an image and is of major importance in the isolation of regions of common property within an image (image segmentation) and subsequent identification or labelling of such regions (image classification) [9]. Functional properties of surface textures in correlation with extracted attributes can form a knowledge base as described in the previous section.

Sensory abilities of living organisms always develop as a consequence of an essential need. As an example, important for the task of texture identification, the abilities of human eye can be useful indication for the texture identification research direction. Human eye can discriminate very small changes in perceived light intensity at high levels of illumination [10]. In the process of learning, human being is trained to correlate specific regular variations of observed object brightness - texture patterns, with material and surface properties. In order to computer mimic the human ability to comprehend the image scene, several methods are used and those which are relevant for our work are presented below.

In the digitalized 8 bit greyscale image each image element – pixel correspond to a value from 0 to 256. If pixels with equal values are counted a greyscale image histogram can be created. Usually histogram is normalised to have values from 0 to 1. From the difference between the histograms on Figure 5(c) and 6(c) it can be concluded, that at proper illuminating conditions unique greyscale histogram is obtained and can be used for imaged surface classification purposes.

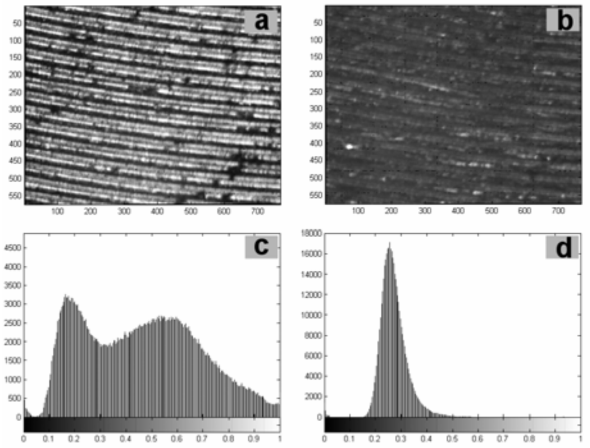

Figure 5. Face turned tool steel, illuminated by the LED light (a, b) and corresponding grey level histograms (c, d). Angle of incidence ϕ: 64.3^o (a) and 38.6^o (b).

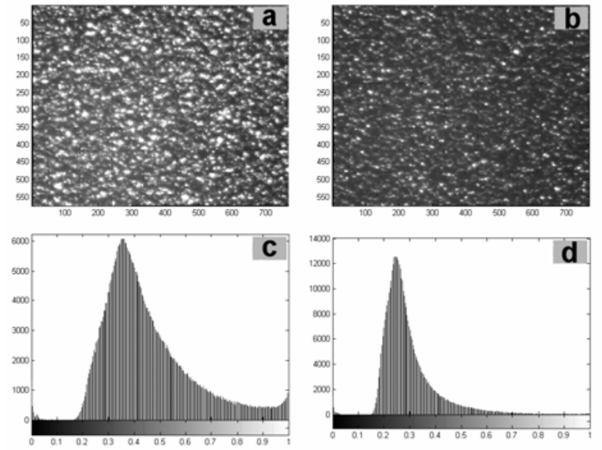

Figure 6. Tool steel machined by EDM, illuminated by LED (a, b); corresponding grey level histograms (c, d). Angle of incidence ϕ: 64.3^o (a) and 38.6^o (b).

5. SUMMARY

An experimental setup and methods presented in this paper will enable objective texture characterisation oriented towards the everyday practice, especially in the domain of tool manufacturing. As continuation of the work several directions can be foreseen. The actual knowledge database is to be created and classification results have to be verified. The other immediate task is to miniaturize the experimental set-up. Regarding the attributes extraction, there are still many attributes to be tested on the texture classification capabilities.

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