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Image Processing of Light-Scattering Images for the Qualitative Surface Analysis

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***Abstract* – Light scattering analysis is already used for roughness measurements, but it is also possible to determine defects on surfaces with this method. Therefore, the scattering distribution is recorded and analyzed using image processing. The defects lead to specific characteristics in the images, which can be assigned to them. In this process the segmentation has an important role because only the best possible separation of the error characteristic leads to good results in the further steps of the image processing chain and in the classification process. For this reason, various segmentation methods were applied to two datasets of images of the scattering distributions and their quality was evaluated by means of the obtained recognition rates.**

I. INTRODUCTION

It is necessary to perform an evaluation based on the surface of a product before the functionality can be analysed. If there are some defects, the entire product is classified as deficient. To ensure that a surface meets the requirements, it must be subjected to a quality inspection. Such a quality inspection can be divided into quantitative and qualitative tests. The quantitative test determines properties like waviness or roughness [1]. In the qualitative test defects such as scratches are searched [2]. There are two ways of performing the tests: tactile or contactless measurements [3]. The first alternative mentioned above is often used for the quantitative testing, whereas the second one may be used for both quantitative and qualitative tests (see [4]).

Digital image processing is an important tool in the non-contact testing; it includes the following steps:

Image acquisition → Image pre-processing → Segmentation → Feature extraction → Classification [5].

The inspection of the surface can be performed not only on the basis of a picture, which represents the appearance, but also with the use of a scattered light image. Although the light scattering analysis is already used for roughness determination, it is also quite possible to use it for the recognition of defects on a surface [3]. This method also provides a solution for the problems of testing reflective surfaces such as shiny metals, transparent or partially transparent glass and plastic materials, as it was described in [6].

After the images are captured and optionally subjected to pre-processing, relevant areas must be selected. It can be done by various segmentation methods. On the basis of this segmentation, the feature extraction and classification are performed. Hence, an error in the segmentation process continues along the image processing chain and significantly influences the classification results. For this reason, the result depends on the quality of the obtained regions. Therefore, the segmentation process should work in a very good way and the regions relevant to partition should be divided as good as possible from the background.

Therefore, it is important to apply different segmentation methods to the images of the scattering distribution and to examine the quality of the results as well as to test their robustness.

II. STATE OF THE ART

A. *Light scattering analysis*

Light scattering analysis has become a powerful tool for the inspection of optical and non-optical surfaces. One important example is the measurement of surface roughness by means of light scattering [7]. The light scattering techniques are non-contact, insensitive against vibrations, and can be used for the characterization of larger surface areas. Light scattering can also be used for detecting and classifying defects. A variety of instruments

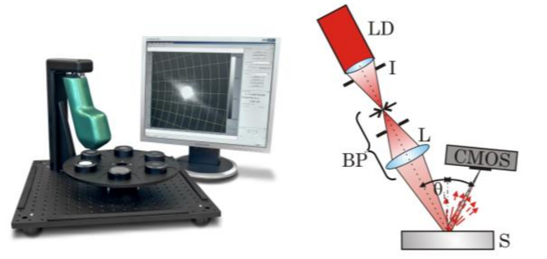

Fig. 1. Possible realization of the light-scatter sensor and a scheme of the functionality of the sensor

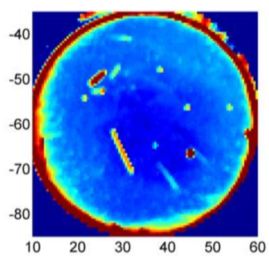

Fig. 2. Scatter map of the polished steel surface

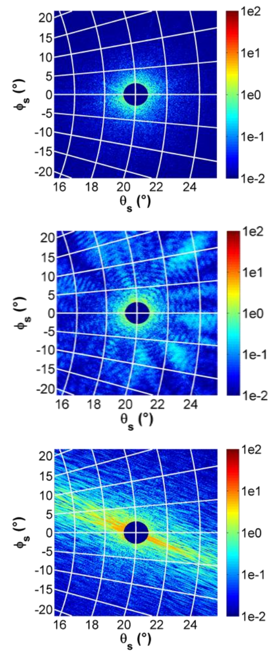

Fig. 3. 3D scattering distribution of three different sources

for angle-resolved light scattering measurements has been developed at Fraunhofer IOF in Jena for wavelengths ranging from the EUV to the IR spectral regions [8].

A compact tool was recently developed at IOF, which allows the rapid inspection of surfaces by means of a matrix sensor approach rather than a scanning detector [9]. *Fig. 1* shows a possible way of realization of the light-scatter sensor and a scheme of the functionality of the sensor. The surface (S) is illuminated with a laser beam (λ = 650 nm) at an angle of incidence of Θ_i = 20°. An iris (I), a spatial frequency filter (BP) and a super-polished lens (L) are needed for producing a clean beam, adjusting the spot diameter and focusing the beam. The specularly reflected beam as well as the surrounding scattered light are recorded by a calibrated CMOS matrix sensor, which consists of 1024 x 1024 single elements. The size of these elements is 10.6 µm x 10.6 µm. A single measurement on an area of about 1 mm in diameter (illumination spot on sample) can be performed within less than one second. Larger areas can be mapped by scanning the sample and recording the scattering distribution as well as the integrated scatter at each point. A resulting scatter map of the polished steel surface is shown in *Fig. 2*.

The homogeneous areas correspond to clean regions and purely roughness-induced scattering. The small regions with enhanced scattering indicate the presence of localized defects (particles, scratches).

In *Fig. 3*, the 3D scattering distribution of three different sources are shown (top to bottom): surface roughness, point defect and scratch.

From the scatter data, quantitative information about the surface imperfections can be derived. For a given surface, the lowest scatter levels usually correspond to purely roughness-induced scattering and the integrated scattered power is directly related to the square of the rms roughness. Even small defects with diameters of a few micrometers lead to a substantial enhancement of the observed scattering. The scatter distributions of point defects are symmetrical with respect to the specular direction whereas the scatter from scratches is strongly anisotropic. These properties can be used first of all to distinguish between these two types of imperfection. Furthermore, the shape of the scattering distribution is related to the structural properties. For point defects, for example, the frequency of the fringes is directly related to the defect diameter. Thus, analysing the scatter images enables sizing or classifying these defects.

B. *Segmentation*

The objective of the segmentation is extracting meaningful regions from image scenes in order to subject them to further analysis. Thus, it is one of the most important steps in the automatic image processing. It separates objects in the order that they can be individually identified and measured [5]. [10] subdivides the methods into point-based, edge-based, region-based and model-based segmentations. The point-based methods include thresholding. The edge-based methods find edges of the regions in the image. Region-based methods begin in the middle of a region and search further points that are connected to the other. In the model-based method, the knowledge of the geometrical shape of the objects is applied for segmentation.

After the segmentation has been made, the question arises concerning the quality of the results. It is difficult to establish the objective criteria, by means of which the success or the quality of segmentation can be evaluated [5]. [4] gives an overview of different possibilities of measuring quality of obtained regions. These are based on the surface areas of the segmented and actually required regions.

C. Random Forest

In some cases, a single tree classifier has an insufficient accuracy, but a combination of several trees and randomly chosen features can improve the results. This is the keynote of random forest classifier. It is based on the bagging and random feature selection. First, the training-set is randomly divided into some subsets and a decision tree is made for each subset. The growth of the trees is performed by means of the random feature selection and the trees remain unpruned. Now every tree can vote for a classification result and the votes are summarized. Because of the assumption that most of the trees make correct decisions concerning the class label, the one with the largest number of votes is elected as the result of the classification. [11]

The random forest classifier has some advantages. For example, it is fast, it has a low number of tuning parameters, it can handle large datasets, it can estimate the importance of variables for the classification, it can estimate missing data and it does not overfit [11], [12].

Our former research on other recognition tasks confirmed this useful behaviour [13], [14], [15], [16]).

III. IMAGE ANALYSIS

A. Image acquisition

The analyzed images were taken by the Fraunhofer IOF in Jena. Therefore, they used the implementation described in II. A. They provided two different datasets. One was a dataset of images of various materials and processing types, for example images of aluminium, turned aluminium, copper, titanium coated material, mirror and black glass. *Fig. 4* shows some examples of the different materials and surfaces. The dataset consists of 968 images, which are divided into four classes. Three of them are defect-classes namely "scratch", "point defect" and "defect combination". The fourth one is the "OK"-class.

A second dataset was required, which includes images of the scattering distribution of one single material and processing type. It consists of 300 images, which are divided into three classes: one "OK"-class and two defect classes – "scratch" and "point defect".

In the presented investigations, only grey-level-images were used.

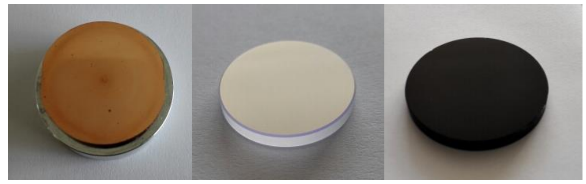

Fig. 4. Examples of the measured surfaces made of different materials

B. Segmentation

Various segmentation methods, which are provided by the image processing software MVTec HALCON 8.0.4, were tested on their suitability for the segmentation-problem. For further studies, 5 of all provided methods with different settings for the first dataset and 7 with different settings for the second dataset were selected. Finally, 12 different segmentations were provided on the first and 11 on the second dataset.

The applied methods will be briefly described below. In the method "Based on Classification," maxima are extracted from the histogram and clusters are formed by them. These clusters correspond to the regions. The "Fast Threshold" assigns the grey values to the regions, which lie between a minimum and a maximum grey value. In "Hysteresis," grey values above a threshold are assigned to the region, the ones below another threshold are discarded. The intermediate grey values are divided by the environment to the region or to the background. The "Automatic Threshold" segments the image with various thresholds, which correspond to the minima of the histogram. In the "Pouring" method, first of all, the local maxima are searched and then the regions based on them are formed. As long as an increase in grey values is given, these points will be assigned to the region. The "Watersheding" initially forms basins. If these are separated by a watershed, the grey value of which is less than a specified threshold, they are recombined in a second step. Regions are thus separated by watersheds, whose grey value is higher than the specified threshold. In the "Dynamic Threshold," the image is segmented with a threshold value, which was automatically determined by means of the minima of the histogram. All the applied methods are described in the release notes for MVTec HALCON 8.0.4 [17].

Depending on the material and processing type as well as different illumination intensities of the images, different forms of defects make it difficult to find a suitable method that works equally well for all images of the scattering distribution. *Fig. 5* shows, for example, an image out of the "point-defect" class. The rings are significant for this type of defect and have to be segmented too. Otherwise, if only the centre point is segmented, the defect looks like a region from the "OK" class. The two images below show the regions segmented by two different methods, in red. The method, which

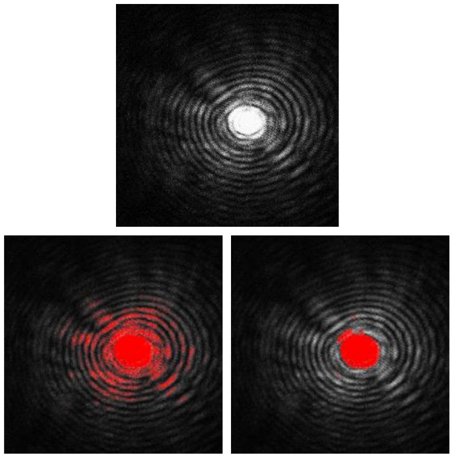

Fig. 5. The image of the scattering distribution of a surface with a point-defect, left: a suitable segmentation, right: an unsuitable segmentation

leads to the segmented region on the left, is suitable because the rings are segmented too. On the right, the centre point is just almost segmented, so this method is unsuitable for the separation of different classes.

C. Feature extraction

The relevant information for the classification of images of the scattering distribution is mainly in the structure of images (texture), as well as in the shape of the regions of higher light intensity, but not in the colour. With the image processing software MVTec HALCON 8.0.4, such feature vectors were created for each image. The vector includes 62 form features, like circularity and convexity. Furthermore, it includes 58 texture features, like Laws texture features. The used feature extraction algorithms are described in the release notes for MVTec HALCON 8.0.4 [17].

D. Classification

The aim of the research is to examine, which segmentation methods are suitable in order to obtain a good classification result. The methods for evaluating the correctness of a segmentation, which were described in [4], are based on the area of the segmented and actually required regions. But it is difficult to set exact boundaries of the meaningful regions in an image of the scattering distribution. Hence, the achieved recognition rate was used as a quality measure for the segmentation process. As only the segmentation quality should be investigated and a ranking of the suitability of different methods should be created, only one classifier was used. Because of the known advantages of the random forest classifier, such as the robustness, the necessity of adjusting a few parameters, thereby providing fast and very good results, it is ideal for these investigations.

The machine learning library Weka 3.7.13 was used for the classification [18]. This process was performed for the feature vectors of each tested segmentation method by means of a 10-fold cross validation 10 times and calculating the average of the recognition rate.

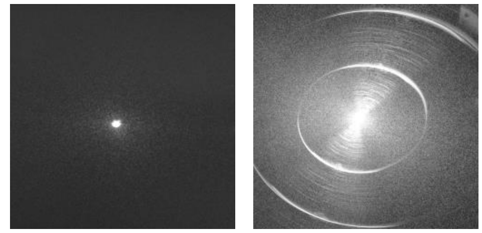

Fig. 6. Comparison of two images from the "OK" class of the first dataset.

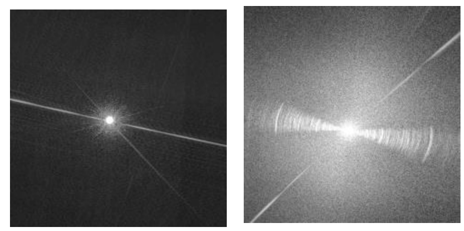

Fig. 7. Comparison of two images from the "scratch" class of the second dataset.

IV. RESULTS

The investigation made with the first dataset was performed with the division into four classes – "scratch," "point defect," "defect combination" and "OK". In a second investigation, the three defect classes were combined into a "not OK" class. It should be tested how good the existence of a defect can be separated from a defect-free surface. The achieved recognition rates are shown in Table 1.

The recognition rates of the first dataset are quite low. As this dataset consists of many different materials and processing types and therefore the characteristics of the defects are different, it is hard to separate the classes in a proper way. With the division into only two classes, higher recognition rates were achieved, but they are still quite low. *Fig. 6* shows the big variety of the appearance of one class; there are two examples out of the "OK" class of different materials and processing types. The left image shows the scattering distribution of a smooth and reflective surface. This good reflectivity causes almost only total reflection and just few diffuse reflection, so there is only a bright point in the middle. The right image shows the scattering distribution of a surface, which was turned. The tool marks are visible and it is still assigned to the "OK" class. *Fig. 7* shows two examples of the scattering distribution of the same material and processing type as in *Fig. 6* if there is a scratch on the surface. The characteristics are quite different again. This reveals the difficulty of classification task and the reason why it comes to misclassifications.

Because of the differences between various materials and processing types, it would be useful to train the classifier separately for each one. Even a division only by material is not enough, since the surface structure strongly depends on the processing type.

Table 1. Received recognition rates with various segmentation methods applied on the first dataset.

Classifier random forest	Average of the recognition rates [%]	
Segmentation method	4 classes	2 classes
Based on classification I	75.10	88.09
Fast threshold	74.80	87.32
Hysteresis	73.59	86.02
Based on classification II	73.3	86.38
Automatic threshold I	73.26	86.14
Pouring with variable interval	72.58	85.33
Fast threshold with variable interval	72.45	84.59
Hysteresis with variable interval	72.21	84.81
Pouring	71.59	84.20
Automatic threshold II	69.55	84.28
Automatic threshold III	69.37	84.44
Automatic threshold IV	69.2	86.79

On the basis of these results, a second dataset, which consists of only one material and processing type, was examined.

The "defect combination" class has been omitted out from this dataset and only the three classes namely "scratch", "point defect" and "OK" were used. In the second investigation, the defect classes were also combined into a "not OK" class in order to determine how well the existence of a defect can be separated from a defect-free surface.

The achieved recognition rates are shown in Table 2.

With the division into only two classes, high recognition rates were achieved by training a classifier for the specific material and processing type. The separation between "OK" and "not OK" works very well. That is quite important for subsequent applications in the industry because the identification of surfaces with defects, which must be removed from the production process, and defect-free surfaces, which can be further processed, is more relevant than the determination whether there is a scratch or a point defect on the surface. This information is relevant for the analysis of the production process and the emergence of defects, but it is not so important as the information about a defect-free or a defective surface

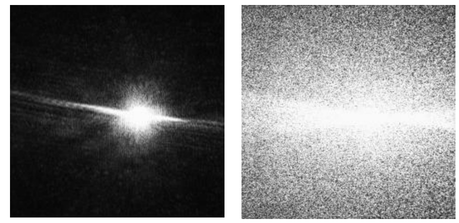

Fig. 8. Comparison of two images from class "scratch"

With the division into three classes, the recognition rates decrease significantly. This shows that the defect classes called "scratch" and "point defect" cannot be well separated. As this dataset consists only of one material and processing type, the characteristics of the "OK" class are almost uniform, so the segmentation and separation from other classes works very well.

Table 2. Received recognition rates with various segmentation methods applied on the second dataset.

Classifier random forest	Average of the recognition rates [%]	
Segmentation method	3 classes	2 classes
Watersheding	93.34	99.10
Fast threshold with variable interval	92.33	98.93
Automatic threshold III	92.23	98.70
Fast threshold	92.03	98.93
Pouring	92.03	98.90
Dynamic threshold	91.97	98.93
Based on classification II	91.90	98.60
Hysteresis	91.27	98.30
Automatic threshold I	90.87	97.96
Automatic threshold IV	90.33	98.30
Hysteresis with variable interval	90.17	98.93

In opposite to the first dataset, the characteristics within the other two classes are relatively similar, but the intensities between the images sometimes fluctuate very much. So a good segmentation and hence the separation of the classes are quite difficult to perform. *Fig. 8* shows two images of the “scratch” class for comparison.

However, the detection rates of the second data set are significantly higher than those of the first one, and it was possible to find some methods, which enable a good segmentation of the meaningful regions.

Some methods that led to good results in the first dataset were less good in the second dataset and vice versa. In the same way, some methods, which worked well for the first dataset, were completely unsuitable for the second one, and other methods could not be applied to the first dataset, but led to good results in the second dataset. It shows once more that the characteristics of the different classes depend on particular materials and processing types. This not only leads to the conclusion that for each material and processing type, the classifiers must be trained individually, but also that the segmentation needs to be performed differently in dependency to the specific characteristic. It takes a long time to find a suitable segmentation method and to set the parameters optimally. For this reason, an automatic method for the segmentation of images of the scattering distribution would be convenient. It should be self-adapting to the prevailing conditions and set the parameters appropriate.

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