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Supporting the Evaluation of Coating Systems through Quantitative Image Analysis of Their Structures

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Abstract. This article presents exemplary methods for evaluating the quality of coating systems using image analysis techniques. It discusses the types of information that can be obtained about the analyzed coating systems, considering different observation approaches and the use of various imaging methods. A typical image processing workflow, designed to enable digital measurements of the examined objects, is also described. The data obtained in this manner provides objective, quantitative information characterizing the analyzed coatings. Although the discussed methods for quantitatively assessing the geometric structures of materials are commonly applied in microstructural analyses, they are still not widely used in other areas. Therefore, the authors focus on demonstrating their potential for assessing the quality of various coating systems.

Introduction

Coating systems are applied to engineering materials as a method to enhance their properties for specific applications [1, 2]. An appropriately chosen and applied coating system enhances the coefficient of friction, increases resistance to atmospheric and environmental conditions, and significantly extends the lifespan of machine components. There are numerous systems of coatings, designed according to the base material [3-5] and the working conditions of the components [6-10]. The deposited surface layers may consist of a single coating applied directly to the substrate or form a multilayer coating system, wherein several layers collectively provide the desired functional properties of the base material. Nevertheless, all of them, at the stage of developing the technology and process adjustments, undergo a set of various mechanical, chemical tests, and structural analyses. A crucial aspect of structural analysis is examining a structure that has been imaged using light or scanning microscopy. Expert visual assessment enables the observation of severe failure in layer adhesion or internal discontinuities. The application of automated algorithms for geometric analysis enables objective and quantitative evaluation of the coatings [2, 11].

The examination of images representing the geometric structure of the analyzed coating systems, performed using image processing algorithms and stereological methods, enables the acquisition of substantially more information than can be discerned by the human eye [22]. Furthermore, it allows for a precise quantitative characterization of the identified layers and their defects. Such quantitative analysis facilitates the monitoring of structural changes within the coating systems as a function of the deposition process parameters, thereby significantly enhancing the efficiency of process optimization [2].

Quantitative image analysis of material structures has been well established in materials science for many years, particularly in determining grain size [12], assessing the content of inclusions in steel [13], or evaluating banding and structural orientation [14]. However, numerous areas remain

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in which digital image processing and analysis methods are applied as part of metallographic investigations, yet are not regulated by international standards. In the authors' opinion, it is also worthwhile to further develop and apply these methods to structural studies in fields that have traditionally relied on visual, expert-based assessment—such as in the case of coating systems. In addition to providing higher accuracy and quantitative characterization, image analysis enables the rapid acquisition of data describing an entire series of images, while ensuring that measurements remain repeatable and objective.

The rapidly developing methods of artificial intelligence and their applications across various fields of science, business, and everyday life may also find use in designing new materials and optimizing their manufacturing processes. However, for this to be possible, it is necessary to provide AI models with numerical data that describes the material structure, which can be utilized during both training and prediction [15-18]. The potential application of AI in materials science constitutes an additional argument emphasizing the importance of quantitatively characterizing the geometric structure of materials at all levels of observation, and consequently, the need to further develop algorithms for their precise description [2].

Materials and Methods

Quantitative structural image analysis of coating systems is performed independently of the base material or coating materials used. However, it is essential to select an appropriate method and observation scale that fully reveal the relevant structural features. Such analysis can be carried out on microscopic images of samples, which represent a perpendicular projection of the surface, a cross-sectional view, or, when feasible, a reconstructed 3D model obtained from tomographic investigation.

An example of surface analysis, presenting a perpendicular projection of the surface, is shown in Fig.1. Such images provide information on the relative porosity, expressed as the ratio of detected pores to the total analyzed surface area, as well as a description of the shape and surface area of each pore. This information enables the assessment of pore homogeneity in terms of its geometric characteristics [20-22].

The image processing procedure employed to obtain the required dataset involved several sequential steps. Initially, the images underwent pre-processing, followed by object detection. Potential artifacts were subsequently removed using mathematical morphology methods. Quantitative measurements were then performed, and the results of the detection were visualized by overlaying the contours of the identified objects on the original image (Fig. 1b).

Cross-sectional analysis enables the measurement of coating local thickness and its heterogeneity, the assessment of coating adhesion to the base material, and the detection of internal defects within the coating, such as microcracks or pores. The procedure for image processing of this type is analogous to that described above for surface analysis: preprocessing, including any necessary filtering and image enhancement, followed by the detection of objects for analysis. For the automatic analysis of geometrical properties, the image must be binary (with pixel values only 0 or 1), as shown in Fig. 2. Pixels representing objects have a value of 1, while pixels representing background have a value of 0. In contrast, those representing the background have a value of 0. On binary images, information on the geometrical shape of the layer is extracted from the background.

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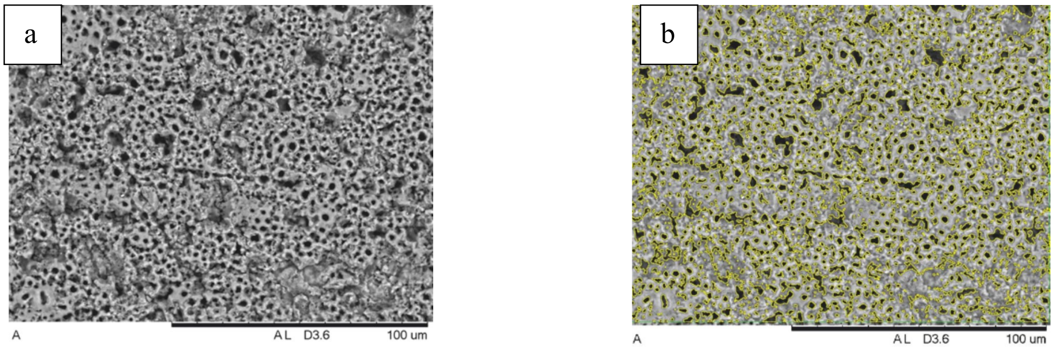

Fig. 1. Analysis of surface porosity a) initial image, b) visualization of detection effects [20].

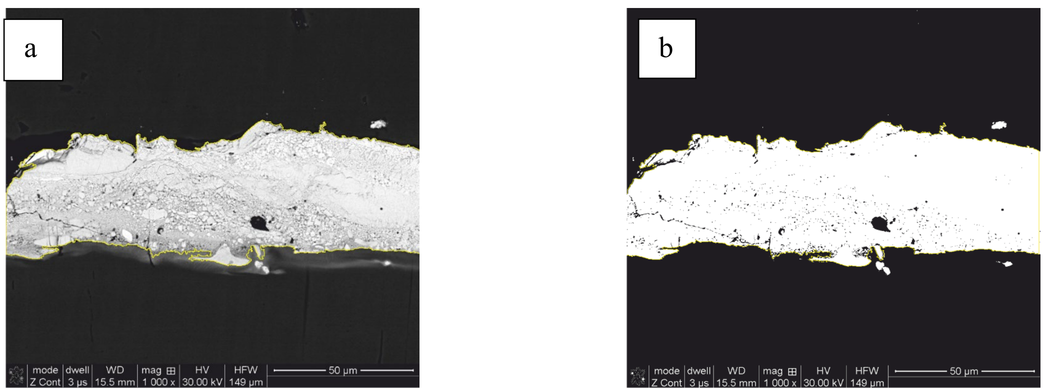

Fig. 2. Analysis of defects in the structure of the WC-Co-Al_2O_3 layer after laser treatment: a) initial image, b) binary image presenting the detected layer.

In a multi-layer coating system (Fig. 3), especially when the image of each layer is difficult to distinguish, visual control analysis of the cross-section profile is helpful, as it presents a profile (Fig. 3). A profile is a chart that displays the change in pixel values along the test line. Analysis of the cure helps to indicate the borders between the layers. Profile analysis may also be used to establish the threshold values for the binarization transform.

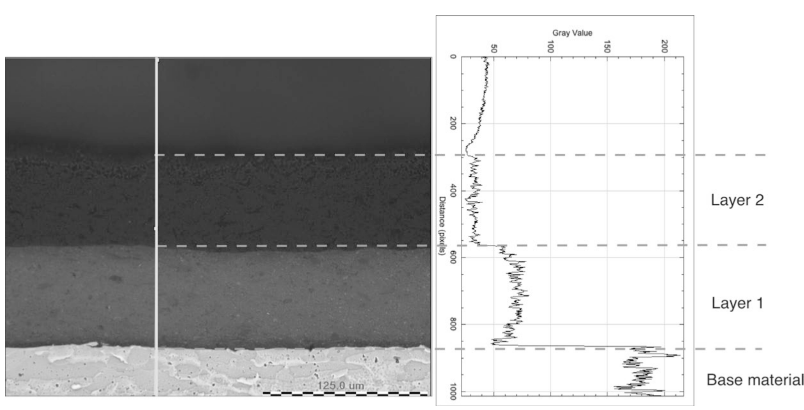

Fig. 3. Multilayer coating system and its profile.

The last method, which is presented in this paper, is a three-dimensional analysis of both the base material and the coatings. Three-dimensional visualization and analysis enable assessment of layer continuity, thickness, and internal defects (Fig. 4) [24].

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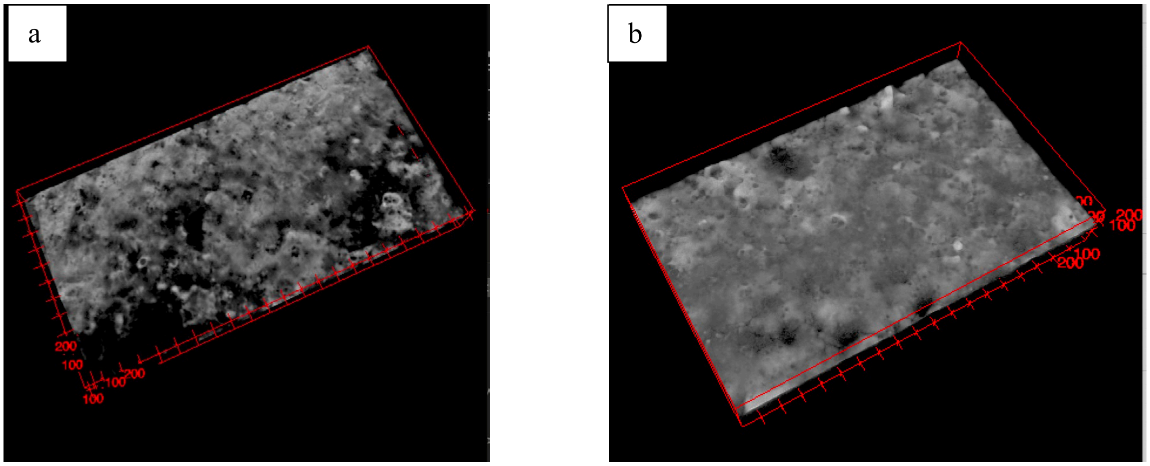

Fig. 4. WC-Co-Al_2O_3 coating before (a) and (b) after laser treatment.

Image Analysis

Depending on the analysis method and research objective, image processing algorithms enable automated detection and quantitative characterization of structural features [21-23]. A standard image processing workflow typically comprises the following stages Fig.5:

1. Image acquisition - The selection of an appropriate observation method should take into account the observation scale and material properties, as well as the way the image is captured as a digital file, with suitably chosen bit depth, color space, spatial resolution, and file format.
2. Image pre-processing – correction of image artifacts using geometric transformations, in the case of optical system-induced distortions, and filtering techniques to reduce noise or enhance contrast between objects and background.
3. Object detection – a set of image transformations aimed at segmenting objects from the background, typically by converting the image to a binary format, in which objects are represented by pixels with a value of 1 and the background by pixels with a value of 0.
4. Digital measurements – selection of measurement algorithms appropriate to the nature of the objects and the specific research goals. Measurements are conducted using stereological methods, which enable the assessment of three-dimensional features based on two-dimensional projections or cross-sections. Standard stereological parameters that deliver information on the analyzed microstructure are: VV - volume fraction of the analyzed phase, NA – number of objects per unit of analyzed area. For three-dimensional image data, direct quantitative information is obtained through volumetric reconstruction of the analyzed objects.

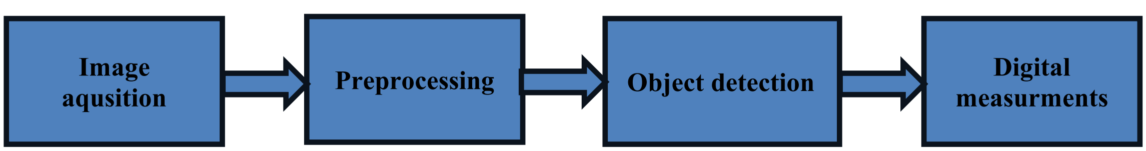

Fig. 5. Scheme of the typical image analysis workflow.

Although the presented general scheme of the image processing algorithm may appear simple, analyzing a specific type of coating system in a given modality often requires the development of a dedicated solution for fully automated processing. While some software packages allow for the interactive adjustment of transformation parameters, which can also yield a dataset that quantitatively describes the objects, human interaction compromises both the objectivity and, most importantly, the repeatability of the analysis. Objectivity, repeatability, and reliability are particularly critical when the analysis aims to generate a dataset from a large number of images for subsequent use in AI-based methods [16-19].

Economic and Technological Impact

The evaluation of coating systems is a key element in quality assessment, both during technological processes [25] and for final products [26]. Human visual assessment always involves an undefined level of subjectivity, which can be reduced by automated image analysis [27,28]. This is particularly important for medium- or high-throughput processes, where subjective visual assessment would be too slow. Examples include processes for applying special coatings [29-31], laser texturing [32,33], or laser remelting of the surface layer [34,35], which result in significant changes to the microgeometry's characteristics [36,37]. Quantitative characteristics obtained from image analysis can serve as observed quantities [38,39] in process optimization methods. Due to the specificity of the data provided, it is sometimes necessary to either support resampling methods [40, 41] or account for the incompleteness of existing knowledge [42, 43]. The end result, however, is a significant improvement in the quality of the final products [44].

Summary

Automated measurements enable the objective evaluation and ensure the repeatability of the measurement process, which is of critical importance during the design phase of coating development and the evolution of deposition technology. Furthermore, they constitute an essential component of quality control in the manufacturing process. The acquired data serve as a valuable source of information regarding the influence of process parameters on the properties of the surface layer, supporting effective modeling of its behavior and performance.

Ongoing research on the application of artificial intelligence for predicting geometric structure aims to optimize the processing parameters of the surface layer while significantly reducing the number of experimental tests required. This approach offers promising prospects for increasing process efficiency and accelerating the development of advanced coating technologies.

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