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A new analysis approach based on Haralick texture features for the characterization of microstructure on the example of low-alloy steels

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A R T I C L E I N F O

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A B S T R A C T

Microstructures were analyzed by an improved texture-based method using gray level co-occurrence matrices (GLCM). This method is based on a new parameter calculated from the stepwise rotation of images and thereby, calculating the values independent of the original texture orientation. The proposed method was applied on a database of etched and scanning electron microscopy (SEM)-imaged low-carbon steel microstructures that are currently extensively used for automated microstructure classification. The results on the microstructures consisting of pearlitic, lath martensitic and lower bainitic constituents revealed that the method allows a significant separation of various types of microstructures in the ideal case of square-shaped cutouts. For complete grains of the corresponding second phases, the results imply that the application of a classifier is advantageous to distinguish them with a sufficient accuracy. The robustness and workability of the method was further demonstrated by discussing the effect of varying the image resolution and contrast/brightness settings during image acquisition. It was shown that such user-dependent setting parameters do not impair the separability of the steel constituents by using the proposed method.

1. Introduction

For future tasks in energy, infrastructure and safety, materials with tailored specifications are necessary. The properties of the materials are controlled by the processing parameters and correlated with the resulting microstructure. In addition to the quantitative analysis of the arrangement, shape and area of the phases, it is also decisive which constituents are present in the microstructure. The clear quantification of these phases is still a big challenge for materials science experts, especially in the field of low-carbon steels where multiple phases are present in a single microstructure.

Fast and reliable differentiation between martensite and bainite is quite problematic and there have been many different approaches to tackle that problem [1–12]. Although discrimination has been possible for a long time by using high-resolution electron microscopy on etched surfaces [12] or in transmission [13–15], these methods are highly cost- and time-consuming and not conducive for daily industrial practice. Therefore, indirect techniques have been developed over time with the aim to make the steel constituents discernible.

Among these, light optical microscopy (LOM) is still the most readily available technique used for steel quantification. Usually, color metallography is used to differentiate complex phase mixtures by their color appearance [6–9,11,16–18]. The analyzed steels generally have higher alloy content leading to the characteristic colors but for low-alloyed steels this is not the case. Because of increased complexity and decreased size of the constituents, the resolution of LOM is not sufficient any longer to separate the marginal differences between the steel phases – especially in the case of bainite and martensite.

To overcome the limit of resolution given by LOM, scanning electron microscope (SEM)-based techniques are increasingly used for steel characterization. One technique in SEM is electron backscatter diffraction microscopy (EBSD), which has been demonstrated to be a powerful tool [1,2,4,5,12,19] in steel characterization. In addition to its higher resolution compared to LOM, it benefits from the fact the steel transformation products like pearlite, martensite and bainite differ theoretically - owing to their formation mechanism - in their defect structure [1]. Moreover, special orientation relationships can be exploited for a phase separation [12]. For example, Gourges et al. [5] and Zajac et al. [12] showed that in the particular case of plate steels, the misorientation profile of martensite and bainite is different. While upper bainite has a high proportion of low angle misorientation, lower bainite has most laths misoriented at 55° and larger. The distinction between lower bainite and martensite is not possible as the misorientation profile is very similar for the two morphologies [5]. One

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drawback of the EBSD technique is its limited sensitivity to fine carbide precipitation in steel, like cementite. However, they are very important to identify certain constituents in low-carbon steels [12,19].

Fortunately, recent advance in adequate etching [17] and high-resolution imaging in SEM make analysis methods feasible that include also image texture. This has already been shown to have a high potential for steel microstructure characterization [10,20–23].

Image texture is the "*spatial arrangement of color or intensities in an image*" [24] and image texture-based analysis methods have been used for image analysis in fields like satellite image classification [25–28] or biomedicine [29]. In the steel community, they can be powerful microstructure descriptors since they are comparatively fast and inexpensive. For instance, Gabor filters have been applied to detect defect structures in steels [30]. By using a multi-dimensional Gabor filter, quantitative values for feature morphology can be derived and used for feature classification [31]. This was used for the classification of carbide distributions in steel by using LOM images. Consequently, ratios for the horizontal-to-vertical energy to estimate the degree of carbide orientation were derived. The fact that the carbides stretched into the rolling direction was exploited by aligning the sample with respect to the image horizontal. The complicating issue for substructures of the various steel constituents is that they do not necessarily orient in the same direction but form in relation to the crystal orientation of the parent austenite grain.

Methods using Fourier transformation are reported to be very effective on regular structure segmentation like pearlite [10] but they fail for noisy images [32] and therefore, are not applicable for SEM images. It is reported [33] that image noise has little influence on the performance of texture analysis with the so-called gray-level co-occurrence matrices (GLCM), originally used by Haralick et al. [27]. Fuchs et al. [21] used the texture feature derived from GLCM to describe the hardening in steel surfaces. Other authors used it for the segmentation of LOM micrographs of multiphase steels via a classification step and reported it to be effective for two-phase steels but not multiphase steels [10]. Dutta et al. [22] showed that the variation of tempering parameters in a fully martensitic steel has a marked influence on the GLCM features of the image texture of representing SEM micrographs.

The use of GLCM features on etched steel microstructures imaged in SEM is promising since the gray-level distribution is very different for the various microstructures on a global scale. Texture features calculated from GLCM are constructed from pixel neighborhood relations in the horizontal, vertical or in the direction of the two image diagonals [27]. As images of the microstructures acquired by microscopy will naturally scatter in image texture orientation from user-to-user, as well as because of different crystallographic orientations within one sample, this will lead to varying texture values even for the same microstructures. Rotation-invariant texture descriptors such as the local binary pattern (LBP) histogram introduced by Ojala et al. [34], can measure the local texture and contrast, but it cannot capture the higher-scale information of structure. Guo et al. [35] therefore combined LBP with a histogram matching to also include global texture orientation into their classification scheme. The orientationally matched and shifted LBP histograms could then be classified based on their differences. But the method will be problematic for textures that do not have any clear orientation to match, which is the case for many of the steel microstructures investigated in the present work.

For evaluation and ensuring good comparability of the image texture of the microscopy images, error-free preparation and adapted etchings are imperative. Because of that, SEM image data must be treated carefully. Owing to limited acquisition time, the grayscale images, which are constructed from point-to-point scanning of an electron beam over the sample surface and the resulting signal intensity of the scattered electrons on the detector, also contain the detector noise. Furthermore, as in the case of the secondary electron contrast, the image results mainly from surface topography which is not only the result of the etched microstructure, i.e. grain/lath boundaries and precipitation, but also all surface artifacts such as scratches, contamination or (local) over-etching. Therefore, the preparation route of the metallographer has a big influence on the visual appearance of the microstructure in SEM. Additionally, etching results depend heavily on the laboratory environment [36]. Due to these issues, standard segmentation algorithms by simple thresholding are usually ineffective in separating the microstructural constituents in steel.

Once the etching has been adjusted and an artifact-free preparation route is established, the regions where the texture analysis will be performed must be determined. In the case of SEM images of multiphase steels with ferritic regions, a threshold level segmentation – typically used in the quantitative microstructure analysis of LOM images – is not possible. The reason is that the ferritic regions show different etch attack corresponding to their crystallographic orientation [37] and this manifests itself in a fine topography contrast in SEM. Since the contrast of the substructure in the carbon-rich phase also mainly results from topography, it is therefore not possible to separate the carbon-rich constituents from the ferritic regions of steel in SEM images simply by applying a threshold level.

A way to overcome this limitation in SEM is to combine images made by different sensors and separate microstructural constituents in a correlative approach of SEM and LOM, as done by Britz et al. in the case of two-phase plate steel microstructures comprised of a ferritic matrix and carbon-rich constituents [38]. Once separated, the substructure of isolated grains can be analyzed using quantification tools. For example, Gola et al. used morphological parameters of single grain objects and their substructure morphology as data to build a classification scheme via a support vector machine (SVM) [20]. A SVM is a binary classification method that takes labeled data from different classes as an input and outputs a model for classifying new unlabeled data into different classes [39]. The inclusion of additional image texture information is promising for further improvement of the SVM performance. In a new approach using a convolutional neural network, the image textures of steel microstructures in SEM have been used to detect and classify regions containing different constituents [3].

The goal of this work is to distinguish between different microstructures based on an improved Haralick image-texture features method. The method calculates a rotation-invariant value with a new approach that uses an image rotation of isolated microstructural objects. This method is applied to the problem of multi-component steel characterization to distinguish the typical constituents, pearlite, martensitic and bainite. The industrial applicability will be discussed by also considering critical user-dependent settings: image resolution and image contrast/brightness. By this approach, valuable information for the distinction of microstructure constituents can be gained.

2. Experimental

2.1. Material

For this study, five images each from six different low-alloyed low-carbon thermo-mechanically rolled steels were acquired using SEM. The samples were produced with different final cooling rates and consisted of two constituents: each ferrite and another carbon-rich steel constituent. Two ferritic-pearlitic sample sets (P1 and P2), three ferritic-martensitic sample sets (M1, M2 and M3) and one ferritic-bainitic set (LB) were used. Fig. 1 shows example images for each of the used sample sets (a full list of all used images is given in the Supplementary materials). P1 (Fig. 1a) was a pearlite sample with straight lamellae, whereas P2 (Fig. 1b) had a more irregular pearlitic structure. M1 and M2 (Fig. 1c and d) are lath martensite samples with smaller martensite packets inside. This contrasts with M3 (Fig. 1e), where the whole of the grains seemed to be built up by a single packet and the martensite had a very regular lath-like structure, which resembled also bainite. LB was a lower bainitic sample. Fig. 2 displays a higher magnification image of LB showing intra-lath carbide precipitation typical for lower bainite