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Automated Quality Assessment of Remelted Steel Ingots

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Abstract— **For high quality steel products it is essential to have specific understanding of the underlying steel production process such as the electric slag remelting process (ESR). To assist the currently manual assessment there is a high need for objective quality measures and standardized evaluation methods. A set of relevant parameters can be derived from the so-called pool profiles that give insight to the remelting process. Based on texture segmentation and ridge detection a computer-vision based automated evaluation of the pool profiles is achieved. A comparison with manually extracted pool profiles from expert metallurgists shows the feasibility of the approach and the good performance of the automated analysis. Further evaluation on different types of steel blocks will yield valuable insight to and improve the overall steel production process.**

I. Introduction and Motivation

The field of quality management and improvement in high quality steel production is one of the deciding reasons whether a steel producer remains competitive or not. In the production of high quality steel products for demanding applications it is essential to remelt conventional produced ingots. In order to yield specific understanding of the remelting process as well as to improve the process, there is a high need for an objective and standardized evaluation of remelted blocks.

The advantage through technology is to be able to substitute pure manual quality control and, thus, very time-consuming work flows. Furthermore, it is possible to provide repeatable calculations of quantitative measurements. This paper presents a vision-based solution to be able to automate those processes.

Currently, most of the structure evaluation is done manually and the information is stored in different analog and digital files. In order to be able to store all information in one place, a software was developed where various different kinds of meta data can be directly mapped to the analyzed steel block.

After a short introduction of the data material (Section II) and a brief overview of related work (Section III), Section IV gives insight into the quality assessment of steel ingots. Section V presents the automated segmentation, Section VI an objective method to derive steel quality parameters and Section VII gives some final conclusions and an outlook on future work.

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II. Data Material

Figure 1 shows the scheme of an ESR. Those remelted high quality steel blocks have a weight up to 20 tons. To analyze the inner solidification of such blocks, it is necessary to saw out longitudinal slices from the center of the block. Furthermore, these plates are cut into pieces to be able to handle size and weight as illustrated in Figure 2.

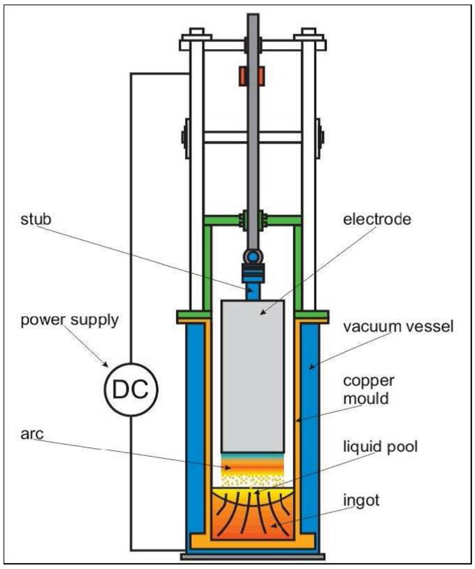


Fig. 1: Scheme of electric slag remelting process.

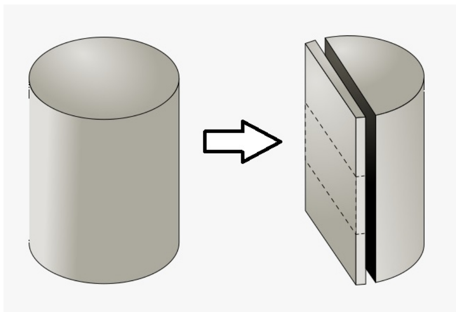


Fig. 2: Preparation of steel blocks for evaluation.

In order to gain deeper knowledge of the remelting process those plates are ground, polished and etched to reveal the inner crystalline solidification structure. Those structures provide information directly linked to the remelting parameters and as a consequence are essential for optimizing these parameters. Changes within the remelting process are directly related to the solidification structure [11], [8]. As a last step, the prepared steel specimen are scanned by a 4k line scan camera. The problem with conventional assessment approaches is that the preparation of the data material is very costly and time consuming. Thus, the available data material for this work consisted of only three blocks with manually annotated ground truth.

III. Related Work

Vision-based approaches are already well established in assessment of material surface characteristics. As well there are also several approaches related to steel quality assessment.

A computer vision based microstructure analysis and classification approach is introduced in [3]. The strategy is to set up a complex histogram representing a 'fingerprint' of a microstructure. With the aid of those histograms it is possible to classify similar texture patterns by calculating the χ^2 distance.

Characterization of steel specimen surfaces are also presented in [2]. Signatures of surface profiles are extracted with multiresolution wavelet decomposition. Furthermore, surface roughness parameters are derived from those signatures.

Another feature extraction from micrographs is elaborated in [7]. The focus within this paper lies on extracting features like grain size, anisotropy of grains and the amount of δ phase.

Further research on vision-based steel surface inspection mainly focuses on the detection of defects. A summary of detectable surface defects and approaches to identify them can be found in [5].

Nevertheless, the proposed methods focus on the analysis of microscopic scale specimens (few mm^2) with their specific microscopic structures or the detection of defects. In contrast, the approach presented in this paper aims at the inspection and analysis of a full steel block with its macroscopic features. Those features exhibit completely different appearances than the microscopic structures.

IV. Quality Assessment of Steel Ingots

Significant parameters for the quality of steel can be derived from so-called pool profiles, which can be derived from inspection of the remelted steel blocks. With the aid of those pool profiles it is possible to determine certain quality attributes within the whole steel block. Therefore the equality of the individual pool profile lines with their surroundings are taken into account. Figure 3 shows manually derived pool profiles of an example steel block plate. These are generated by human experts (metallurgists) who try to identify the growth direction of the dendrites[1] in the image. Based on those direction vectors, lines in predefined distances are estimated perpendicular to the vectors. This process is very time consuming and prone to human error. Furthermore, the results are influenced by subjective interpretation and, thus, experts easily end up with diverse results.

[1]Dendrites are complex three-dimensional tree-like structures. Dendritic morphology is the most commonly observed solidification structure [9], p. 78.

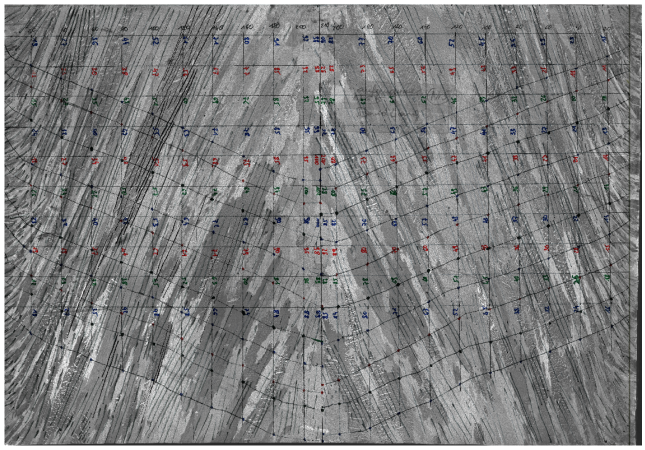


Fig. 3: Manually derived pool profiles.

Further ground truth data analysis revealed that some blocks show much more irregularities on top, bottom and in the middle due to the globular solidification in those areas. To be still able to extract meaningful pool profiles, metallurgists disregard those areas and simply classify pool profiles in regions with trans-crystalline solidification only. This basically means that trans-crystalline solidification areas provide representative information, whereas globular areas are basically unstructured and as a result do not provide meaningful information for the pool profiles. Thus, for an objective evaluation it is essential to automatically distinguish between globular and trans-crystalline solidification areas.

V. Steel Specimen Segmentation

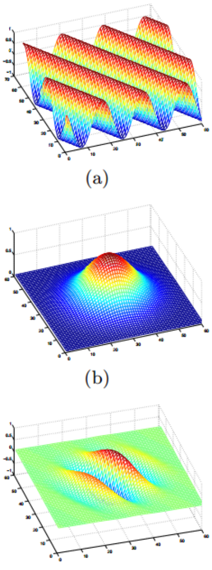
The consequential first step of the automated quality assessment is the segmentation of globular and trans-crystalline solidification areas. The main idea for automated segmentation is based on the different textural appearance (regular and irregular patterns) of the different solidification regions. Therefore, various algorithms for the description of the surfaces were selected. The resulting classification gives information about where the actual extraction of information used for pool profile generation/calculation can be retrieved from.

Due to the lack of extensive ground truth data, it was necessary to find suitable texture features and to implement customized classification methods rather than to train already existing classifiers. The following sections give an overview about the selected algorithms and the respective evaluation results.

A. Gabor Filter

The basic idea of using Gabor filters was to analyze spatial frequencies and their orientations within image patches. Trans-crystalline solidification areas represent areas with clearly visible frequencies and orientations whereas globular solidification areas do not. 2D Gabor filters are sinusoid functions combined with a Gaussian (see Figure 4) [6].

Two classes of training patches were created for globular and trans-crystalline solidification areas. These patches



(a)

(b)

(c)

Fig. 4: Gabor filter composition: (a) 2D sinusoid oriented at 30° with the x-axis, (b) a Gaussian kernel, (c) the corresponding Gabor filter [6].

were used to generate covariance descriptors of Gabor filter outputs with one frequency and six orientations. Nearest neighbor classification was used for evaluation.

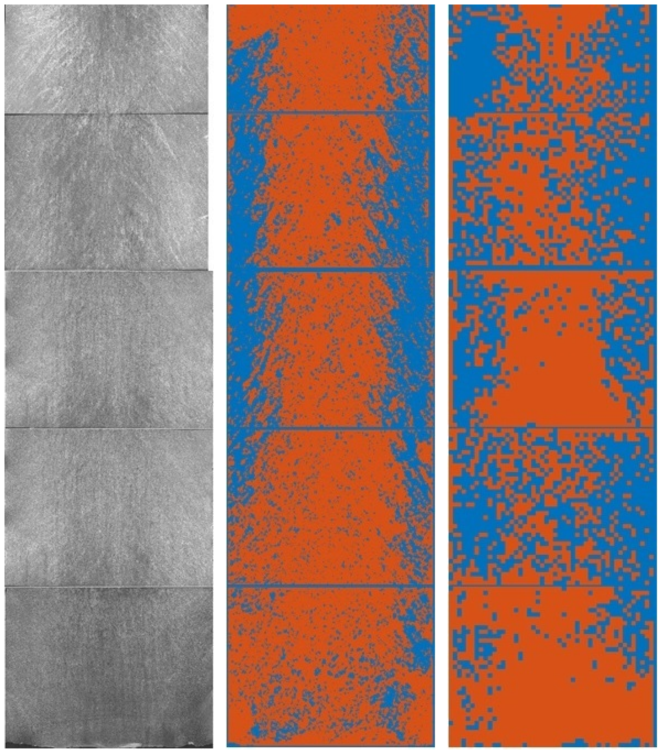
Figure 5 shows a whole steel block and the segmentation results. From Figure 5b it is obvious that the classification output delivers plausible results for the trained type of steel, although the trans-crystalline areas are not perfectly classified if the orientation of the solidification structure does not perfectly match the trained ground truth data.

B. Spatial Filter Bank

The paper presented by Ahmadvand and Daliri [1] introduces a way to perform invariant texture classification by using a spatial filter bank in multi-resolution analysis. The generated features comprise l_1-norm, standard deviation and entropy calculated from the spatial filter bank results of the original patch and the discrete wavelet transformed patch. Proposed filters are Gaussian, Laplacian of Gaussian and local standard deviation.

Same as for Gabor filters, two different patch classes are used to set up two feature matrices. For classification simple Mahalanobis distances between the feature vector and the matrices are calculated to determine class affiliation.

Although certain regions (middle and bottom in Figure 5c) are extracted more homogeneously than in the Gabor filter approach, the classification output does not yield a satisfactory result as it is too dependent on selection of training patches. The filter bank matches good within direct surroundings of training patch areas, whereas other areas cannot clearly be separated.



(a) Original image.

(b) Gabor filter output with nearest neighbor classification.

(c) Spatial filter bank output with Mahalanobis distance classification.

Fig. 5: Original image and segmentation output.

C. Local Binary Patterns (LBP)

LBP [10] are used to describe the surrounding of a pixel. This is done by comparing a pixel to each of its neighbors (which [10] defines by radius and number of points on the consequential circle). Given eight neighbors LBP result in an eight digit binary number where each digit gives information about whether the center point value is greater/equal or smaller than its neighbor. To retrieve information about a larger area LBP for each pixel in that area are summed up in a histogram illustrated in Figure 6.

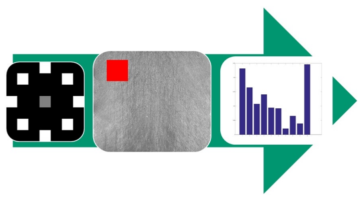


Fig. 6: LBP histogram generation.

To be able to determine certain edge and line information of an area's histogram, we decided to summarize inverted patterns, same orientation patterns or patterns that just describe noise. Overall dominating bins like noise and white/black dots are deleted from the histogram. Following those steps, it is possible to determine features (histogram bins) that correlate with the desired regions.

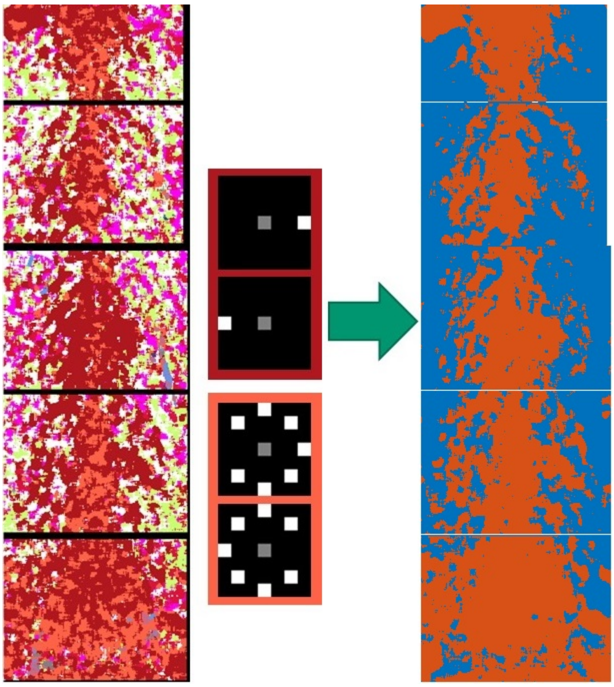


Fig. 7: LBP dominating feature/bin output.

Figure 7 shows a color coded image on the left hand side where each color matches a bin from the summarized histogram. The output image on the right hand side was generated by using a majority filter calculating the dominating feature for a specified area around a center pixel and then plotting its assigned color in the output image. The background colors of the illustrated patterns (in the middle) correlate with the colors in the left image. Together they represent the orange area within the final binary output image on the right. It is clearly evident that horizontal lines (line endings) smoothly correlate with globular solidification areas whereas trans-crystalline areas are dominated by other orientations.

D. Feature Comparison

Experiments with different steel compositions have shown that the Gabor, as well as the spatial filter bank approach, do not deliver generic solutions. Even for equal types of steel with other block dimensions, those algorithms do not deliver satisfying results.

Interestingly, the discovery that dominating horizontal orientations correlate with the globular solidification area, was also proven for further steel blocks. The validation of the segmentation output was performed by metallurgists visually. Thus, the segmentation based on LBP (Figure 7) is used as basis for the quality parameter extraction.

VI. Pool Profiles

As previously mentioned, pool profiles are used to determine quality parameters. Therefore, a fast and reliable process that can produce repeatable results with a minimum need of human interaction is required.

The best performing method during analysis of different steel types is based on a combination of scale-space and ridge detection. The ridge detection is similar to a biometric fingerprint recognition approach [4] with the difference that in this application regions with constant directions are important, whereas in fingerprint recognition characteristics like crossing points or ridge ends are relevant.

A. Ridges and Orientations

The algorithm for ridge preparation, extraction and orientation calculation is based on a paper presented by Hong, Wan and Jain [4]. They show a way to identify and normalize ridge regions within an image and to calculate their orientations. Figure 8 illustrates the process of pool profile derivation on a small sample sector of a steel specimen.

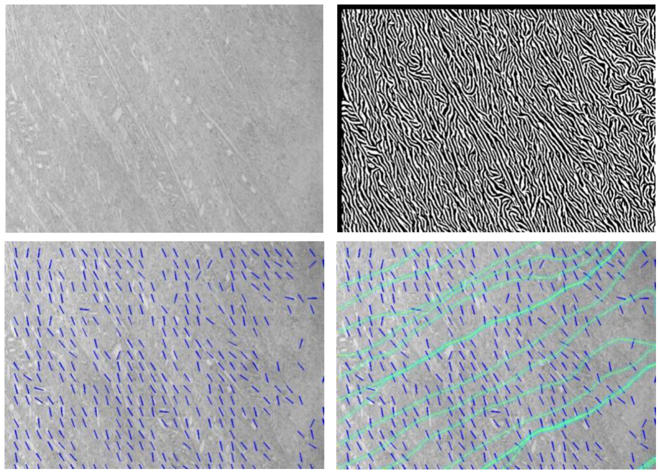


Fig. 8: Pool profile detection by ridge analysis. Top: Sector of steel specimen and derived ridges. Bottom: Derivation of orientations and final pool profile.

B. Orientation Filtering

The cutting or etching process in preparation of the steel sample or the imaging/scanning process itself can lead to artifacts. In order to handle those problematic areas, it is necessary to implement a filtering algorithm for the ridge orientations.

The first step of optimization takes place during preprocessing and delivers a mask of non-valid areas through a gray scale segmentation process performed on a smoothed and re-sampled image of the steel specimen.

The second step is the filtering of derived orientations. This filtering relies on homogeneity properties of the orientations in image areas. If an orientation vector is not in conformity with its surrounding/neighboring orientations it is treated as outlier and, thus, filtered before deriving the final pool profile.

Additionally, as a third step orientations are calculated on different scales of the image to pre-filter orientations deviating from smaller scales.

Figure 9 shows a sample steel plate and the calculated orientations (short blue lines) with and without filtering. It is clearly evident that areas with little or even no information content were masked out. The resulting orientations are smaller in number, but more expressive.

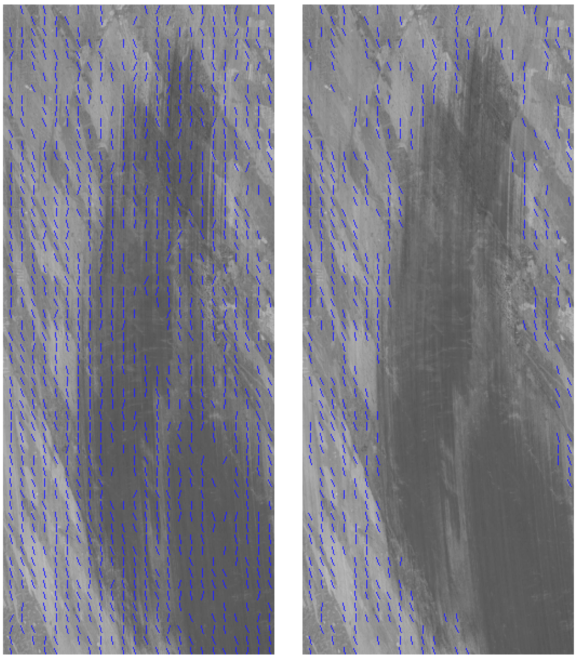


Fig. 9: Optimization of orientation detection. Left: Result without filtering. Right: Result with filtering.

C. *Pool Profile Results*

The pool profile itself comprises of trace lines derived from ridge orientations. Each trace line is calculated from a given individual starting point by calculating a normal on the underlying orientation to the consequential next one and so forth. The calculation begins either from the outer borders (left and right) to the middle or vice versa. Figure 10 shows an example of automatic generated pool profiles overlaid on automatically detected orientations. The two colors of the trace lines represent the different starting orientations.

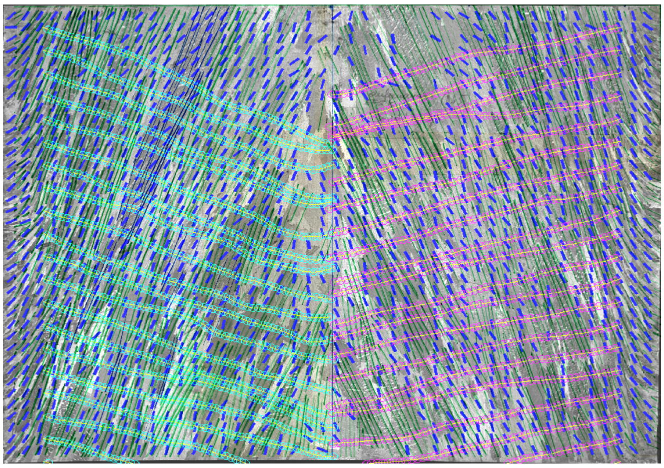


Fig. 10: Automatic generated pool profiles from the sample steel block displayed in Figure 3.

Metallurgists verified the quality of this approach by comparing the manually derived ground truth (Figure 3) with the achieved results (Figure 10). The comparison shows the good correspondence of manually generated ground truth with automated derived pool profiles.

VII. Conclusions and Outlook

This paper presented algorithms to perform steel specimen segmentation for classification of globular and transcrystalline solidification areas and algorithms to automate pool profile generation. Figure 11 displays a whole steel block with segmentation and pool profiles. The automated quality assessment is currently under evaluation by metallurgists on additional steel blocks.

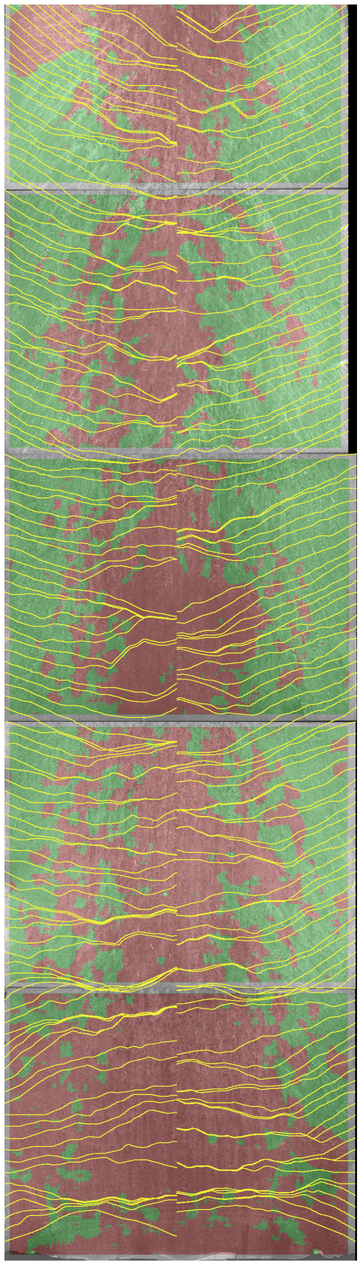


Fig. 11: Final result with segmentation and pool profiles.

First feedback indicates that the method for segmentation and pool profile generation is applicable for a wide range of steel products. This might require further implementations and/or parametrization for segmentation and pool profile generation. In the future, as image acquisition will take place regularly and, thus, more data will be available, we intend to investigate approaches based on deep learning, that will enhance automated segmentation and quality assessment even further.

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