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Determination of the phase proportions of austenitic steels using artificial intelligence

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Summary

Work on the development of an automated process for the metallography of metallic materials based on digital image processing and artificial intelligence is presented. This particularly involves the precise recording of the phase components of duplex stainless steel by evaluating metallic micrographs. The process can also be applied to other types of steel and other metallic materials.

Keywords: Metallography, Duplex Stainless Steel, Image Processing, Artificial Intelligence, Machine Learning

Motivation

Currently known evaluation strategies are based on algorithmic or visual methods for determining phase components of metallographic samples. Such as shown in Fig. 1.

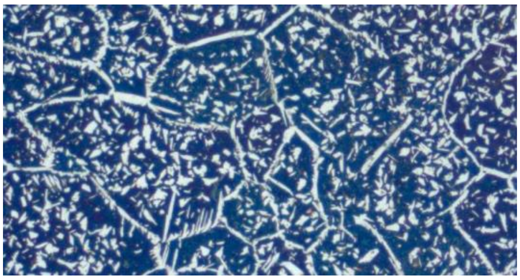

Fig. 1. Color-etched section of a sample of austenitic steel, magnified 500x

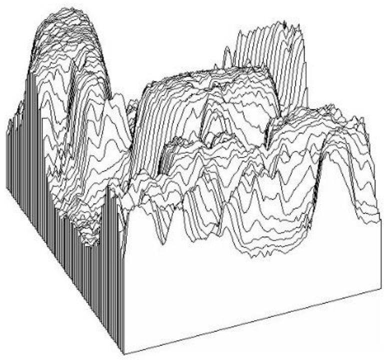

Fig. 2. Gray value distribution of the pixel amplitudes of an image section in Fig. 1

A recognized method is the point counting method, in which selected points of the microscope image of a sectional sample are visually examined by a measuring person and assigned to a phase [1]. However, this process is very complex and requires a lot of personnel. Automated evaluations are based on algorithmic methods such as threshold determination of the gray value histogram of metallographic images [2] or segmentation using edge detection. However, since the distribution of the pixel amplitudes is irregular (see Fig. 2), these methods have limits in terms of the achievable accuracy. Learning processes and artificial intelligence processes are therefore proposed as an alternative. The initial goal here was to achieve at least the same level of accuracy as the visual procedures.

Approach

The approach consisted of using artificial intelligence in the form of model-based and learning processes including neural networks, with the focus on the latter. The following methods, not based on neural networks, were examined: Support Vector Machine SVM [3], decision trees (random forest), Chan-Vese method [4]. In addition to some of the procedures, relaxation labeling – RL was used. In addition, various filter operators known from image processing were used to filter the images before further processing. The histogram method according to Otsu was also examined for comparison. A convolutional network was used as the neural network (convolutional neural network - CNN, see Fig. 3).

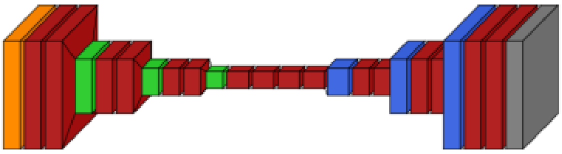

Fig. 3. Convolutional neural network used

orange: input layer, red: folding layers, green: pooling layers blue: upscaling layers, gray: output layer

In addition, a modified version was used, containing 21 layers each. In addition to the fully connected layers known from classic neural networks, they also contain mathematical convolution layers, pooling layers for data reduction and upscaling layers. The “Tensorflow” framework was used for this. A program was created in Python from Anaconda that can be used to access Tensorflow and configure networks. To obtain the image material for the investigations, material samples measuring approximately 10x2 mm2 were embedded, cross-sections were made and the samples were then color-etched. Microscopic images were then taken at 500x magnification and an image resolution of 2646 x 2056 pixels for further evaluation. In the learning methods, a training process was initially carried out using labeled pixels, i.e. pixels of known class affiliation (austenite or ferrite). To determine the actual class affiliation of these reference pixels, software was developed with which areas in pixel blocks of size 128 x 128 are marked using mouse support based on visual assessment and this area is then assigned to a phase. All pixels contained in the pixel block are then labelled and can be used as reference pixels. In addition to the real data from the metallographic samples, artificially generated images were also used to obtain reference patterns using so-called image augmentation [5].The systems of the learning procedures have now been trained with the help of the reference patterns provided. With the Support Vector Machine - SVM, individual pixels were trained and with the neural networks, blocks of 128 x 128 pixels were trained. Finally 128 x 128 pixels were available as a result at the network output.

Results

The individual methods were applied to labelled pixels in several images, as shown in Fig. 1). Understandably, the learning processes only used pixels that were not previously included in the training process. For the evaluation, the accuracy was determined, i.e. the number of correctly assigned pixels to the austenite and ferrite classes, based on the number of all evaluated pixels, also the pixels incorrectly assigned to the two classes. Table 1 shows the results for the individual procedures. For the methods not based on neural networks, only the best results are shown depending on various parameters. As can be seen, the accuracy results are all between 95% and 98%, which is in line with expectations. The best results were achieved with the modified convolutional neural network.

Tab 1. Accuracy values achieved for the examined procedures, RF – Random forest, RL Relaxation labelling

Procedure (see section Solution approach)	Accuracy
OTSU	0.956
ChanVese	0,960
ChanVese+RL	0,968
RF	0,973
CNN	0,973
CNN modified	0,977

Outlook

The actual work builds the foundation for the automatic determination of phase proportions in duplex stainless steel. Future work will concern further areas of application in metallography and ceramography as well as further increases in accuracy. Folding neural networks in particular still have great potential for this. Further possible future applications are the detection of grain and phase boundaries, the detection of alloy components and the detection of voids also in X-ray, CT or ultrasound images.

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