Surface Topography: Metrology and Properties

PAPER

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To cite this article: Xu Zhenying *et al* 2018 *Surf. Topogr.: Metrol. Prop.* **6** 025001

IOP Publishing Surf. Topogr.: Metrol. Prop. 6 (2018) 025001 https://doi.org/10.1088/2051-672X/aab73b

Surface Topography: Metrology and Properties

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RECEIVED
2 November 2017

REVISED
9 March 2018

ACCEPTED FOR PUBLICATION
16 March 2018

PUBLISHED
13 April 2018

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Algorithm based on regional separation for automatic grain boundary extraction using improved mean shift method

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Keywords: grain size, metallographic images, image processing, mean shift

Abstract

Metallographic microscopy shows that the vast majority of metal materials are composed of many small grains; the grain size of a metal is important for determining the tensile strength, toughness, plasticity, and other mechanical properties. In order to quantitatively evaluate grain size in metals, grain boundaries must be identified in metallographic images. Based on the phenomenon of grain boundary blurring or disconnection in metallographic images, this study develops an algorithm based on regional separation for automatically extracting grain boundaries by an improved mean shift method. Experimental observation shows that the grain boundaries obtained by the proposed algorithm are highly complete and accurate. This research has practical value because the proposed algorithm is suitable for grain boundary extraction from most metallographic images.

1. Introduction

Metallographic analysis is an important means for testing the performance of metal materials. To obtain metallographic images, the target metal is subjected to intercepting, grinding, polishing, and etching, and is then placed in a metallographic microscope. The vast majority of metals are composed of many small grains visible through metallographic microscopy. The interfaces of adjacent grains are called grain boundaries [1]. Traditional materials theory holds that the conventional mechanical properties of fine-grained materials, including the tensile strength, toughness, and plasticity, are relatively good. The grain size also affects the fatigue strength of the metal. In order to measure the size of grains conveniently, it is particularly important to extract grain boundaries accurately and effectively.

Computational methods are important in analyzing metallographic images. However, because of the processes of sample preparation and data acquisition, the grain boundaries in metallographic images are often blurred and cannot be directly and completely extracted [2]. Much research has been done in order to identify clear and complete grain boundaries. At present, mainstream research proceeds in two directions. First, by segmenting the grains in metallographic images, a section of the complete grain structure can be obtained. The main algorithmic methods used are watershed segmentation [3], level-set segmentation [4], and clustering. Second, certain operators are used to extract grain boundaries directly from metallographic images; these include the Canny [5], Sobel, and Kirsch operators. The method based on clustering [6, 7] divides a dataset into several subsets according to the similarities of elements. For example, Zhang [8] reported some success using a fuzzy C-means algorithm to segment metallographic images of 12Cr1MoV steel. However, segmentation methods still entail much error in the extraction of grain boundaries. The gradient operator method [9, 10] is among the most commonly applied image processing techniques, using a grayscale version of the image to obtain edge features. The Canny operator can be used for this purpose; however, accurate grain boundary extraction is impeded by noise in metallographic imaging, which causes the boundaries to appear blurred and incomplete.

The existing algorithms used for grain boundary extraction have achieved ideal effects in certain metallographic images. This study presents a fast and accurate algorithm developed for grain boundary extraction in order to process metallographic images of different types and characteristics. The metallographic images are divided into multiple regions by using the marker-based watershed algorithm, and a mean shift algorithm is used to segment the grains in each region. Experimental observation shows that the

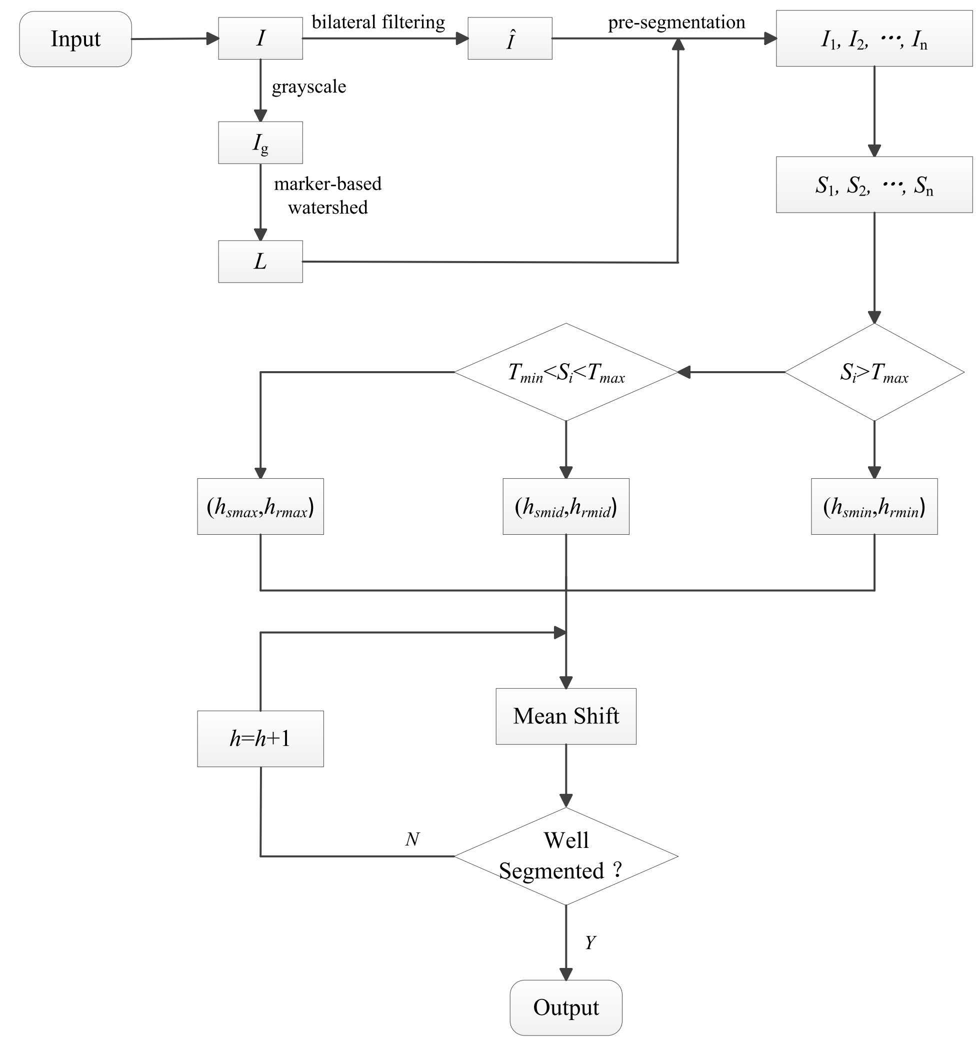


Figure 1. Flowchart of the algorithm.

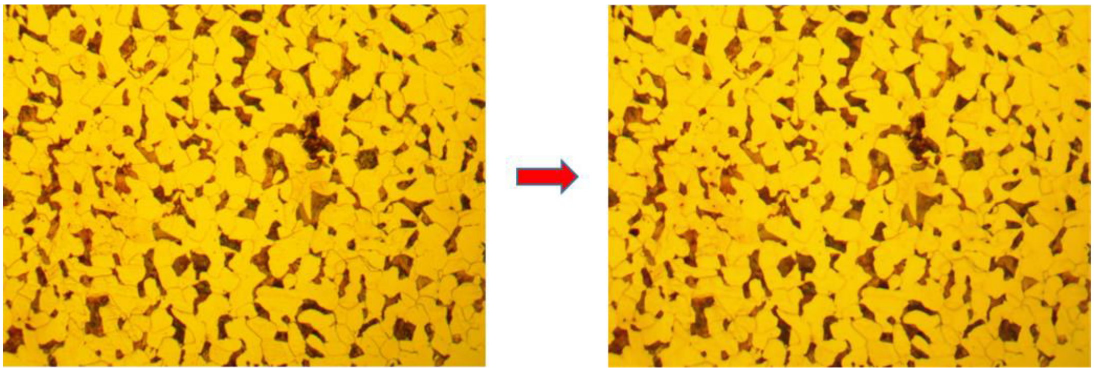
grain boundaries obtained by the algorithm proposed in this study are much more complete and accurate compared to those identified by other algorithms.

2. Development of the algorithm used for grain boundary extraction from metallographic images

Unlike ordinary digital images, a metallographic image mainly depicts grains and grain boundaries; each grain is similar except the shape. Because of interactions between various grain structures, the boundaries between adjacent grains are not always obvious. In applying a traditional mean shift algorithm for metallographic image segmentation, some clusters may have link channels connecting them; that is, some grains cannot be accurately and effectively separated. In this research, de-noised metallographic images are pre-segmented and divided into multiple regions, before an improved mean shift algorithm is used to segment the grains according to the characteristics of each region. The boundaries between grains are identified as the final grain boundaries. The specific steps of this algorithm are shown in figure 1.

2.1. Preprocessing of metallographic images

Metallographic images are mainly obtained by metallographic microscopy. In this research, metallographic images of 20# steel are selected as main experimental objects, as shown in figure 2(a). Because of hardware and software interferences, digital compression, and other reasons, metallographic images always contain noise, affecting the image quality. Therefore, the images must be well filtered to extract the grain boundaries more accurately. The main problem in using common filtering algorithms is that the details of the original grain boundaries in the image are unclear; filter processing generally increases blurriness. This complicates the subsequent grain boundary extraction process and increases error. Therefore, this research uses an algorithm with an edge-preserving function called color bilateral filtering, a nonlinear filtering algorithm containing information on both spatial and color domains.



(a) (b)

Figure 2. Effects of filtering. (a) Original image; (b) color bilateral filtered image.

The performance of the color bilateral filtering algorithm depends on the setting of the initial parameters. Figure 2(b) shows the effect of color bilateral filtering. Compared to other filtering algorithms, it does not overly blur the image, and the image retains fine grain boundaries.

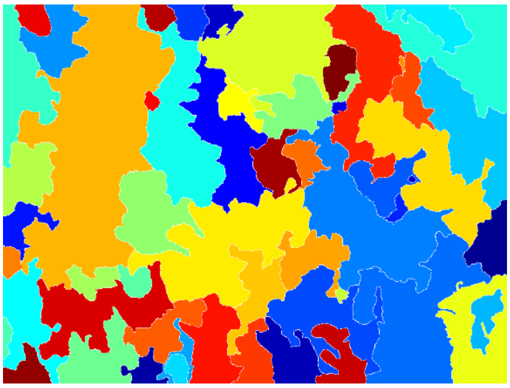


Figure 3. The contour of region.

2.2. Grain boundary extraction based on mean shift

Mean shift is a nonparametric fast pattern-matching algorithm based on kernel density gradient estimation. Image segmentation often utilizes mean shift algorithms; the image data is subjected to multiple iterations through the kernel function to achieve convergence. After convergence, the cluster centers whose spatial domain and color domain are similar are merged and then split.

In order to find the cluster center, the mean shift algorithm mainly uses kernel functions to iterate the image data and thereby achieve convergence. In the iterative process, the selection of the spatial domain bandwidth parameters h_s and color domain bandwidth parameters h_r has a crucial effect on the results. Many experiments have shown that excessively large bandwidth parameters extend the clusters along the clustering points, impeding classification. On the contrary, excessively small bandwidth parameters lead to over-segmentation.

In order to solve the problem of bandwidth parameter selection, this study uses the marker-based watershed algorithm to pre-segment the original metallographic images after grayscale transformation, and to obtain the contours of regions after pre-segmentation. The marker-based watershed algorithm is based on the watershed algorithm, not only eliminating object edge information loss, but also effectively solving the problem of over-segmentation inherent in traditional watershed algorithms. Firstly, the algorithm uses the Sobel operator to filter the gray-scale transformed images in the horizontal and vertical directions, and calculates the model value to obtain gradient magnitude images. Then, the foregrounds and backgrounds of the grayscale images are marked using morphological reconstruction techniques. After that, using the mathematical morphological minimum calibration technique, the acquired foreground objects and background objects are force-set as local minima of the gradient magnitude images, and all local minima are masked to suppress the phenomenon of excessive segmentation. Finally, the modified gradient amplitude images are segmented by a traditional watershed algorithm. Figure 3 shows the contours of regions after pre-segmentation. The preprocessed image can be divided into many regions according to the contours.

Considering the particularity of metallographic images, a mean shift algorithm based on the adaptive selection of bandwidth parameters is proposed. The main steps are as follows:

(1) According to the region contours of grayscale metallographic images after pre-segmentation, the color metallographic images are divided into n regions: $I_1, I_2, \ldots, I_n$;

(2) The area S_j of the square I_j, where $j = 1, 2, \ldots, n$, is calculated. $S_{\min}$ and $S_{\max}$ denote the smallest and largest areas, respectively; figure 4 shows the statistical chart of the region area;

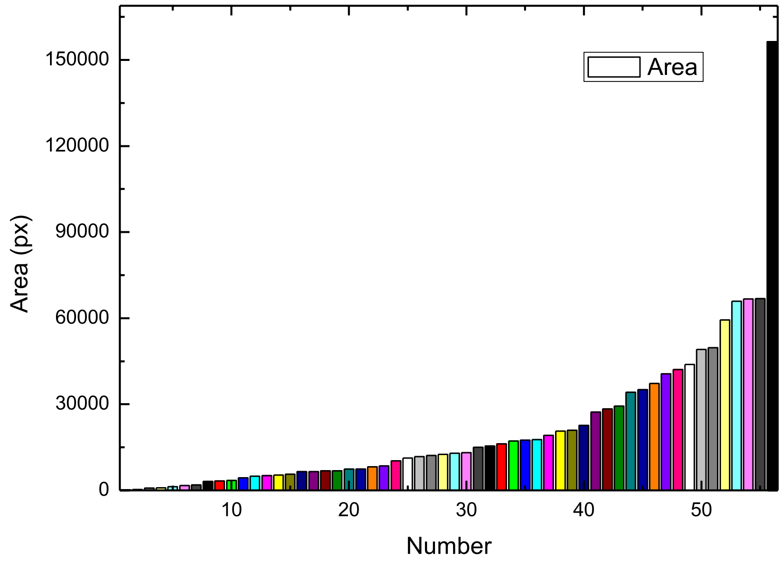


Figure 4. Statistical chart of region area.

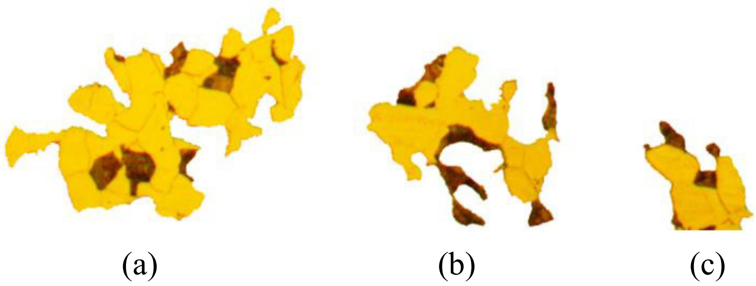


Figure 5. Three different region areas.

(3) Each area S_j is compared with the two area thresholds $T_{\min}$ and $T_{\max}$ to determine the bandwidth parameters h_s and h_r, using the following relationships:

$$h_s = \begin{cases} h_{s\min}, S_j > T_{\max} \\ h_{s\mathrm{mid}}, T_{\min} \leqslant S_j \leqslant T_{\max} \\ h_{s\max}, S_j < T_{\min} \end{cases},$$

$$h_r = \begin{cases} h_{r\min}, S_j > T_{\max} \\ h_{r\mathrm{mid}}, T_{\min} \leqslant S_j \leqslant T_{\max} \\ h_{r\max}, S_j < T_{\min} \end{cases},$$

and

$$\begin{cases} 5 \leqslant h_{s\min} \leqslant 8, 5 \leqslant h_{r\min} \leqslant 10 \\ 9 \leqslant h_{s\mathrm{mid}} \leqslant 12, 11 \leqslant h_{r\mathrm{mid}} \leqslant 15 \\ 13 \leqslant h_{s\max} \leqslant 15, 16 \leqslant h_{r\mathrm{mid}} \leqslant 20 \end{cases},$$

where

$$T_{\min} = S_{\min} + \frac{1}{3}(S_{\max} - S_{\min}),$$

$$T_{\mathrm{miax}} = S_{\min} + \frac{2}{3}(S_{\max} - S_{\min})$$

and h_s and h_r denote the spatial and color domain bandwidth parameters, respectively. Initially, the corresponding minimum values are assigned as the bandwidth parameters. Figure 5 depicts the extraction of three different regions based on pre-segmentation;

(4) The mean shift algorithm is used to segment each region, accurately and efficiently separating areas of grains. The area of each grain Z_l is calculated, where $l = 1, 2, \ldots, num$; num denotes the number of grains after segmentation. The ratio $\frac{Z_e}{Z_f}$ is calculated, where:

$$1 \leqslant e \leqslant num, 1 \leqslant f \leqslant num, e \neq f$$

(5) $\frac{Z_e}{Z_f} \geqslant 2$ and $\frac{Z_e}{Z_f} \leqslant \frac{1}{2}$ indicate over-segmentation and under-segmentation, respectively. In such cases, the bandwidth parameters are re-determined as $h_s = h_s + 1$ and $h_r = h_r + 1$, before repeating step 4. When $\frac{1}{2} < \frac{Z_e}{Z_f} < 2$, the bandwidth parameters are suitable and the grains are well segmented; region segmentation is then complete.

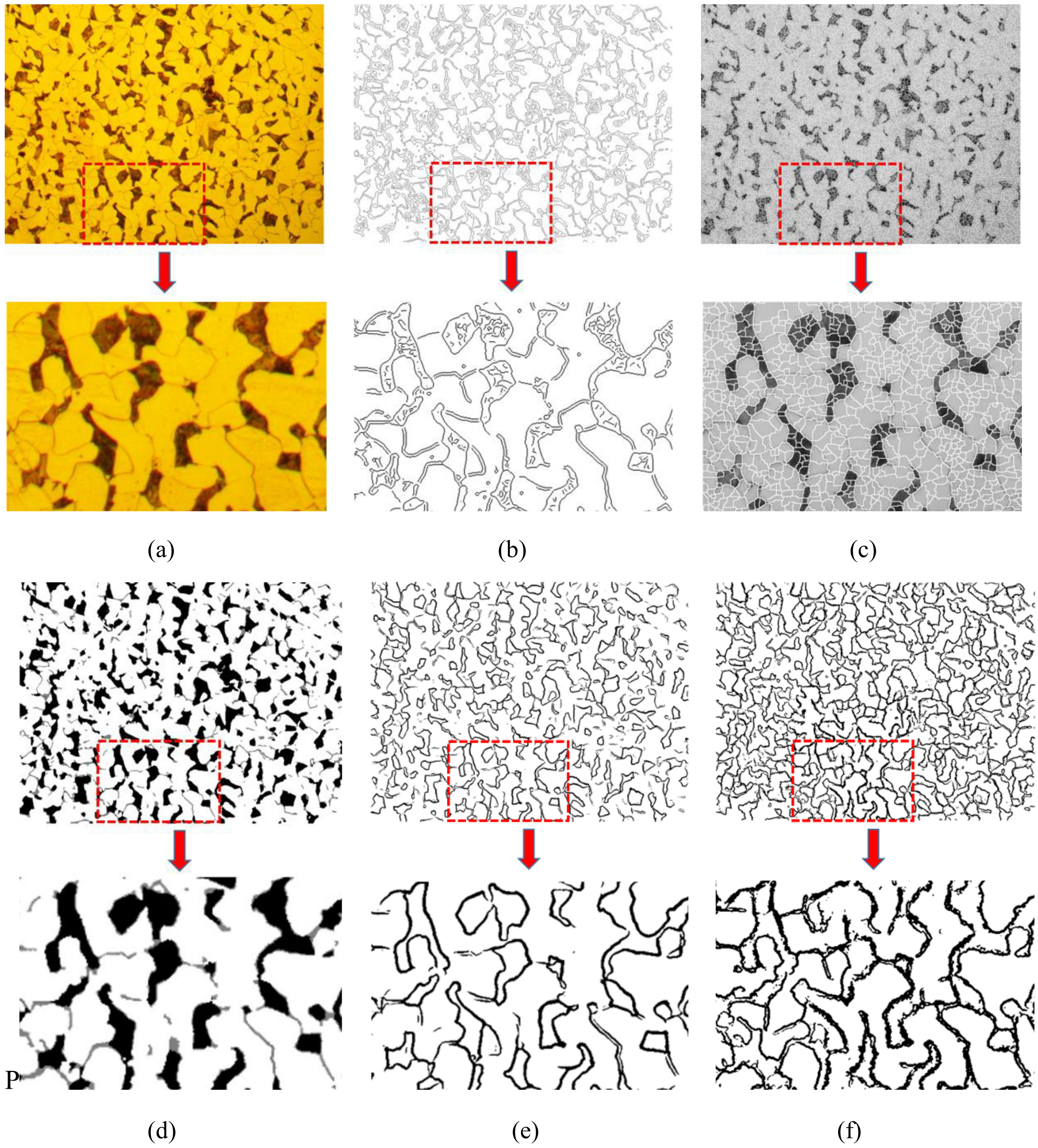


Figure 6. Results of grain boundary extraction by different methods: (a) Original image, (b) Canny operator, (c) watershed algorithm, (d) level-set algorithm, (e) random forest algorithm, (f) proposed algorithm.

Table 1. Comparison of the performances of different algorithms used for grain boundary extraction.

Algorithm	Number of pixels	Matching rate (%)	Number of grains	Average area of grains	Running time
Drawn by hand	184238	100	478	2185	2 h
Canny operator	74659	15.41	371	3111	1 s
Watershed algorithm	204652	89.97	1976	518	5 s
Level-set algorithm	165471	56.64	401	2652	48 s
Random forest algorithm	179854	61.97	459	2275	2 s
Proposed algorithm	195449	69.13	498	2075	10 s

At this point, a section of the grains in the metallographic image is isolated and the boundaries between each grain form the final grain boundaries.

3. Experiment and analysis

In this study, prepared experimental samples are placed on an inverted metallographic microscope (MR5000), the metallographic microscope is adjusted to collect experimental images in different environments, and most of the images are resized to 1280 × 960 pixels. In order to verify the feasibility and efficiency of the proposed algorithm using these experimental images, many related experiments were performed in this study. The software environment for these experiments was MATLAB 2012b, and the computer

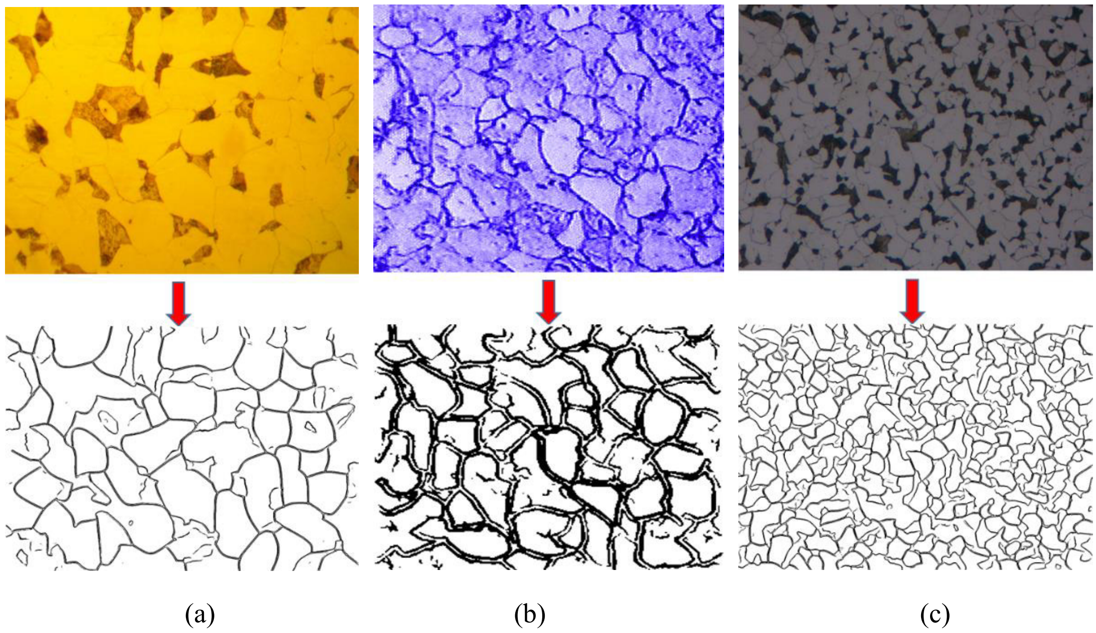


Figure 7. Results of grain boundary extraction from different metallographic images. (a) 55# (b) 20CrMnTi (c) CF53.

used a 2.10 GHz Intel® Core™i3-2310M CPU with 6 GB memory.

3.1. Contrast experiments of grain boundary extraction

Figure 6 shows the results of grain boundary extraction using a number of existing algorithms. Figure 6(a) depicts an original metallographic image of 20# steel; figure 6(b) shows the grain boundaries obtained by the Canny operator; figure 6(c) shows the applied improves traditional watershed algorithm; and figure 6(d) applies the improved level-set algorithm described in [4] to segment the metallographic image. Dollár and Zitnick [11] proposes an edge-detection algorithm based on machine learning; figure 6(e) shows its application in grain boundary extraction. Figure 6(f) is the effect of the algorithm described in this report. For convenience of observation and comparison, the same area in each processed image is enlarged. The Canny operator extracts many pseudo-grain boundaries; the traditional watershed algorithm produces serious over-segmentation; and the level-set algorithm can only extract the complete grain boundaries of ferrite. The grain boundaries extracted by the random forest algorithm, one of the most famous machine-learning algorithms, are incomplete with some broken boundaries. The existing algorithms all show many problems in grain boundary extraction, while the algorithm proposed in this study yields more complete and accurate results.

3.2. Performance analysis of each algorithm

As shown in figure 6, the algorithm proposed in this study extracts more complete grain boundaries, but direct observation is overly subjective. In this research, the performances of the algorithms used for grain boundary extraction are analyzed based on the following aspects: number of grain boundary pixels, matching rate, number of grains, average area of grains, and running time. The metallographic image used in the experiments cannot be used for direct comparison because it is not a standard image. Therefore, this study uses an image depicting grain boundaries extracted by hand as the true value of the data for comparison with other algorithms. This image was provided by three senior metallographic analysts and the hand-drawn grain boundaries are relatively complete. Therefore, the data can be used as objective criteria for analyzing grain boundary extraction.

The second column in table 1 represents the number of grain boundary pixels extracted by different algorithms; the value should be within 1228800, which is the number of pixels in the total image. The third column in table 1 represents the rate of correct matches between the grain boundaries extracted by different algorithms and those extracted by hand. This value represents the ratio of extracted to correct grain boundaries. From the table, the algorithm proposed in this study is second only to the watershed algorithm in accuracy. While the matching rate of the watershed algorithm reaches 89.97%, the algorithm extracts many grain boundaries, both correct and incorrect, mainly because of excessive segmentation. We only considered the number of correct grain boundaries in proportion to the number of grain boundaries extracted by hand when calculating the correct matching rate; thus, the matching rate of the traditional watershed algorithm is higher. Therefore, this data column can be used as a criterion for evaluating the algorithms used for grain boundary extraction.

The microstructural study of steel is helpful in understanding the characteristics of steel. The size

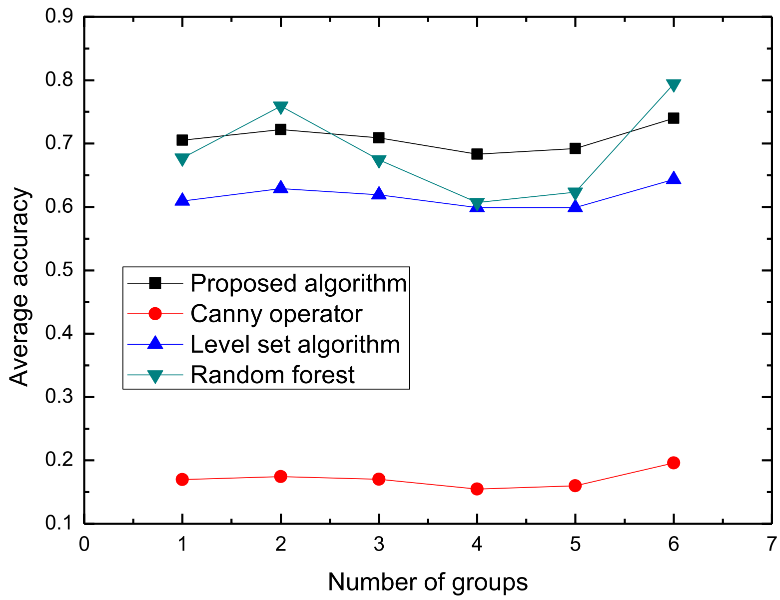


Figure 8. Line chart of average accuracy of different algorithms.

and number of grains observed in metallographic images can directly affect the rating of the material. The fourth and fifth columns in table 1 represent the number and average area of grains. The values of these two columns represent the judgment of grain boundary extraction. By comparing these two values, a slight over-extraction phenomenon is found in the algorithm proposed in this study, while the level-set and random forest algorithms cannot extract all grain boundaries completely. The last column shows the running times, or the speed of different algorithms in processing the same image; these can describe the operating efficiencies of the different techniques. The running times for the Canny operator and random forest algorithm are shorter than those of the others, requiring only 1–2 s to complete. The running time of the proposed algorithm is 10 s, shorter only than the level-set algorithm and hand-drawing techniques. Although the proposed algorithm is not the fastest, it meets actual industrial needs.

In order to test the reliability of the above algorithm, six different types of steel samples are prepared and metallographic images are collected under different illumination conditions, magnifications, and corrosion conditions. The accuracy and stability of the algorithm used for grain boundary extraction are compared by selecting 10 micrographs of each kind of steel as testing images. Figure 7(a) shows the effect of grain boundary extraction from 55# steel under 200× magnification; figure 7(b) shows the effect of grain boundary extraction from a 300 × 250-pixel image of 20CrMnTi# steel; and figure 7(c) shows the effect of grain boundary extraction from CF53# steel under low-light conditions. As the figure shows, although the materials, light environments, and image sizes are different, the grain boundaries extracted by our algorithm are still relatively complete.

Figure 8 shows the average accuracy of each algorithm in the grain boundary extraction of different types of metallographic images. As the over-segmentation of the watershed algorithm is very serious and the results obtained are not accurate, it was not selected for comparison. Through observation and comparison, it is apparent that the algorithm proposed in this study has relatively high accuracy and good stability in application to different types of metallographic images. Based on the above experiments, the algorithm proposed in this research is superior to existing algorithms, and is suitable for grain boundary extraction from metallographic images.

4. Conclusion

Grain boundary extraction is an important part of grain size analysis in material science. In this research, a method used for grain boundary extraction with high speed and high accuracy is proposed. The marker-based watershed algorithm is used for pre-segmentation of metallographic images, and then the grains are segmented by using an improved mean shift algorithm based on the characteristics of each region. Through comparison experiments with existing algorithms, the proposed algorithm can effectively extract grain boundaries and enhance grain boundary integrity in application to a variety of metallographic images.

Acknowledgments

This paper is from the project from Science and Technology Support Program of Jiangsu province (No.BY2015064-02), the project from Practice and Innovation Program of Jiangsu Province (No. SJLX16_0447).

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