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An Improved Iterative Watershed According to Ridge Detection for Segmentation of Metallographic Image

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Abstract—Metallographic images of metal crystal structures which have disconnected boundaries and heterogeneous intensity need to be segmented and analyzed to estimate the materials' performance. Comparing to other image segmentation methods, the watershed segmentation algorithm (WSA) has so far dominated in the segmentation of metallographic image based on seeds growing. However, an object in metallographic image with poor quality has more than one seed, so objects in the image will be over-segmented into several parts so that it becomes even hard to identify the segmentation result. Hence the traditional iterative watershed segmentation algorithm (TIWSA), a revised watershed algorithm, has been designed to mitigate the over-segmentation dilemma by classifying and merging pseudo-blobs to surrounding blobs. However, during the process of pseudo-blobs combination in TIWSA, a pseudo-blob may falsely be merged into a surrounding real-blob due to noises and textures in the image, so the TIWSA has to reduce combinations of pseudo-blobs in order to assure the accuracy of merging process so that the over-segmentation dilemma cannot be eradicated. Hence the TIWSA needs to be revised to protect the real-blobs and prevent them from merging other pseudo-blobs. This paper, aiming at this problem, firstly represents a new principle called *real-blob classification rule* to classify the real-blobs based on the iterative prior probability of real-blob. Once a new blob is formed, it will be examined whether it is a real-blob and all real-blobs will be recorded. Secondly, the pseudo-blob merge rule is revised that the recorded real-blobs canno longer merge other pseudo-blobs during the process of pseudo-blobs combination. The result shows that this improved TIWSA not only avoids wrong merging, but also maximizes the number of the pseudo-blobs elimination which mitigates the over-segmentation dilemma in TIWSA.

Keywords--segmentation of metallographic image, iterative watershed algorithm, ridge detection, real-blob classification.

I. Introduction

Metallography is an academic subject to study the physical structure and component of metallic materials from both macrostructure and microstructure, which is based on the photographs taken under the microscope [1]. The photographs show the distribution of metal crystal structures (MCS). Different sizes of MCSs correspond to different uses. What's more, metallic materials which have similar sizes of MCSs always have superior quality.

The statistical data and measurement of MCSs are finished by manpower all along, including area, diameter, orientation, and so on. Since the MCSs in the photograph have different shapes and sizes with irregular distribution, counting and measuring theses blobs are always heavy tasks with low precision. With the development of image segmentation, manpower can be saved by computers, using the technology of image segmentation and analysis. On the one hand, it avoids false manual operations which cause inaccurate; on the other hand, it can reduce the workload of the operators and achieve automatic process of metal casting as well. In order to realize the automation of image processing by computer, image segmentation is the first and most imperative step to identify and analyze the MCSs in the picture.

In image processing literature, the segmentation is well-studied and has been divided into several main categories [2]:

1) Threshold-based method is easy to implement and very efficient for images containing distinct objects in a contrasting background. In this algorithm, the optimum threshold separating objects and background is calculated to minimize their intra-class variance. In metallographic images, however, textures in the metal blobs lead to heterogeneous intensity of pixels in the blobs. What's more, in the process of photographing, the uneven illumination and noise make difficult for threshold-based segmentation algorithm to achieve a satisfactory result.

2) Edge-based method [3], which based on edge information, is a well-developed scheme in image processing. Since an intensity impulse often exists

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between the object and background, the edge-based method detects the impulse in a certain orientation to trace the object boundaries. However, the edges in metallographic images are often disconnected, while this method needs closed region boundaries to trace.

3) The clustering methods, for example. the K-means algorithm, choose cluster centers and assign each pixel in the image to the cluster, which minimizes the distance between the pixel and the cluster center.

4) Region growing method [4] is based on the seed growing principle. The regions are iteratively expanded by comparing all unallocated neighboring pixels to the regions. The segmentation results are dependent on the choice of seeds, so the noises in the image can lead to poor results.

5) Watershed segmentation algorithm regards the gradient scale of an image as a topographic surface. Pixels with the highest gradient magnitude intensities correspond to watershed lines, which signify the region boundaries [5]. And local minima of image gradient which mark the initial objects achieve the segmentation by region growing. However, an object in metallographic image with poor quality has more than one local gradient minimum, so every object in the metallographic image will be over-segmented into several parts. Hence the TIWSA, a revised watershed algorithm, has been designed to solve the over-segmentation dilemma by merging pseudo-blobs into surrounding blobs to improve the accuracy and the results of image partition.

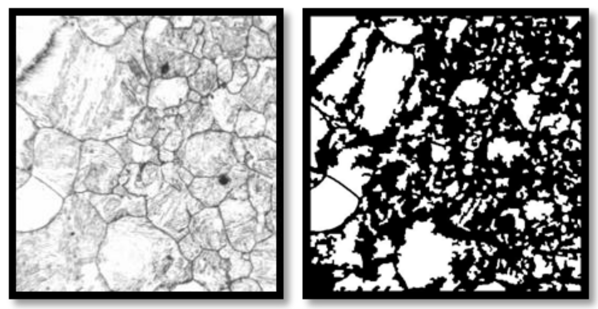
To sum up, as Metallographic images have disconnected boundaries, irregular shapes and heterogeneous intensity, traditional algorithms hardly achieve effective and accurate segmentation. Comparing to other image segmentation methods, the TIWSA has dominated in segmentation of metallographic image [6], however, it cannot eliminate the over-segmentation dilemma, which still impacts the accuracy of the segmentation. This paper presents an improved TIWSA to process the real-life metallographic images.

II. Traditional Iterative Watershed Segmentation Algorithm

In order to remove the pseudo-blobs caused by over-segmentation in watershed segmentation algorithm, the TIWSA based on seed growing and ridge detection appends pseudo-blob classification and merge rules which apparently improve the exactness of segmentation.

2.1. Seed detection

In the TIWSA, the seeds which are exactly the local minima of image gradient, as the lowest water-basin which marks the initial segmentation object, achieve the segmentation by region growing. As the pixels in the MCSs are much brighter than in the boundaries, seeds can be identified automatically by double-threshold (intensity threshold and area threshold) approach. The morphological extended-maxima transform with intensity threshold is used to find the regional joined components. Holes whose area is less than the area threshold in the blob will be eliminated. As a result, a binary image after seed detection will be got which is shown in Fig. 1(b).



(a) (b)

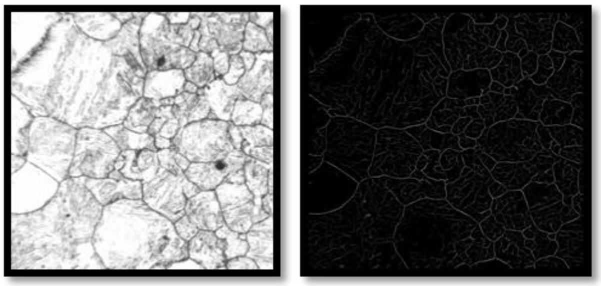
Fig.1. The Seed Detection Process (a) Original image (b) Seed detection by double-threshold approach

2.2. Ridge detection

Ridge is superimposed as the highest waterline in the image at the first time watershed transform to assist the segmentation and play an essential role in pseudo-blobs classification. As the boundaries are relatively evident and robust with constant intensity (dark) and width among the cluttered MCSs in metallographic images, it is easy and efficient to utilize the ridge detection instead of edge detection for the irregular shapes and discontinuous boundaries as stated previously.

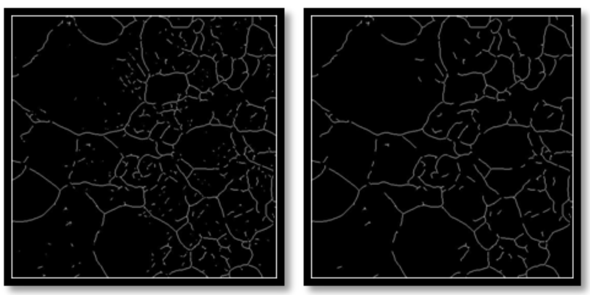
Mathematically, the ridge is defined as the local extreme point in the direction of the largest surface curvature and it can be detected by computing the eigenvalue of the Hessian matrix, which is shown in Fig. 1 (b).

Since the boundaries have larger eigenvalue of the Hessian matrix than the stripes and noises in the blobs have, ridge can be extracted by an appropriate threshold using threshold-based method which is shown in Fig 2 (a). Finally, the ridge can be more precise after "region-open" morphological operation to



(a) (b)

Fig. 2. Ridge Detection Process (a) Original image (b) Ridge detection image by computing the eigenvalue of the Hessian matrix



(a) (b)

Figure 3. Extract the Ridge (a) The first step of ridge extraction using threshold-based method (b) The second step of ridge extraction using "region-open" morphological operation

remove small stripes and spots caused by the noises and textures in the blobs in Figure 3(b).

2.3. Iterative Scheme

In order to solve the over-segmentation dilemma and improve the accuracy further, an iterative scheme is proposed with pseudo-blob classification rule and pseudo-blob merge rule. The first one identifies the over-segmented blob, named as pseudo-blob. The second principle reallocates the pixels of pseudo-blobs into other blobs to form integrated correct blobs, named as real-blobs [7].

2.3.1. Pseudo-blob classification rule

Define V_s as the feature vector extracted from image pixel at location $s=(x,y)$ and iteration time t. For a blob, the posterior probability of V_s from the pseudo-blob b_p or real-blob b_r respectively

$$P(b_p \mid V_s, t) = \frac{P(V_s \mid b_p, t)P(b_p \mid t)}{P(V_s \mid t)} \tag{1}$$

$$P(b_r \mid V_s, t) = \frac{P(V_s \mid b_r, t)P(b_r \mid t)}{P(V_s \mid t)} \tag{2}$$

Using the Bayes decision rule, the pixel will be classified as inside a pseudo-blob if the V_s satisfies

$$P(b_p \mid V_s, t) > P(b_r \mid V_s, t) \tag{3}$$

Be aware that the feature vector V_s associated the pixel $s=(x,y)$ is either from a real-blob or a pseudo-blob, which follows that

$$\begin{aligned} P(V_s \mid t) = {} & P(V_s \mid b_p, t) \times P(b_p \mid t) \\ & + P(V_s \mid b_r, t) \times P(b_r \mid t) \end{aligned} \tag{4}$$

Taking all the pixels in a pseudo-blob into account, and substituting (1) and (4) to (3), it becomes

$$2P(b_p \mid t) > \frac{\sum_{s \in b_p} P(V_s \mid t)}{\sum_{s \in b_p} P(V_s \mid b_p, t)} \tag{5}$$

The prior probability of pseudo-blob at iteration t is updated recursively using

$$P(b_p \mid t) = \alpha P(b_p \mid t-1) \tag{6}$$

$$\alpha = \left(\frac{\alpha_0}{P(b_p \mid 0)} \right)^{1/N} \tag{7}$$

where N is the maximum number of iterations, and $P(b_p \mid N) = \alpha_0$ at the final iteration.

For simplicity, feature vector V_s is chosen as the binary ridge descriptor in this work, i.e.

$$P(V_s \mid t) = \begin{cases} 1 & s = ridge \\ 0 & s \neq ridge \end{cases} \tag{8}$$

2.3.2. Pseudo-blob merge rule

There are two basic rules to regroup the pixels inside a pseudo-blob which are pixel-by-pixel and all pixels as a whole. In this work, the later one always gives reasonable results. Therefore, the proposed merge rule is based on "winner-take-all" principle.

(1) Label the pixels inside pseudo-blobs as blank.
(2) Re-watershed the blank in the image to let the surrounding blobs encroach the pseudo-blob pixels.
(3) Count the pixels encroached by the surrounding blobs and compute the rate. The surrounding blob which has the biggest rate will be the winner.

(4) Assign the winner's label to all pseudo-blob pixels.

2.4. The drawbacks of TIWSA in application

The prior probability of pseudo-blob is a fundamental parameter in the iterative scheme that can mitigate the over-segmentation dilemma, as the pseudo-blobs are identified and merged based on this parameter. Whereas when it continuously grows, the TIWSA may erroneously merge a pseudo-blob into a nearby real-blob because the noises and the blob textures in metallographic photographs impact the processes of pseudo-blobs identification and re-watershed. Hence we have to reduce this parameter to a proper size using the TIWSA in order to guarantee the real-blobs, although reducing this parameter will left some pseudo-blobs in the image.

III. Improved Iterative Watershed Segmentation Algorithm

To get rid of the drawbacks of TIWSA mentioned above and promote the accuracy of partition, this paper proposes a new principle called the real-blob classification rule and the pseudo-blob merge rule is revised according to the proposed rule.

3.1 Real-blob Classification Rule

The Real-blob has already had a correct form, thus any combination with other pseudo-blobs will destroy its correct shape and boundary. Similar to pseudo-blob, the real-blob is identified by the prior probability of real-blob which is computed as follow:
V_s is the feature vector extracted from image pixel at location $s=(x,y)$ and iteration time t . Using the Bayes decision rule, the pixel will be classified as inside a real-blob if the V_s satisfies

$$P(b_r \mid V_s, t) > P(b_p \mid V_s, t) \qquad (9)$$

Substituting (2.2) and (2.4) to (3.1), it becomes

$$2P(b_r \mid t) > \frac{\sum_{s \in b_r} P(V_s \mid t)}{\sum_{s \in b_r} P(V_s \mid b_r, t)} \qquad (10)$$

The prior probability of real-blob at iteration t is updated recursively using

$$P(b_r \mid t) = \beta P(b_r \mid t-1) \qquad (11)$$

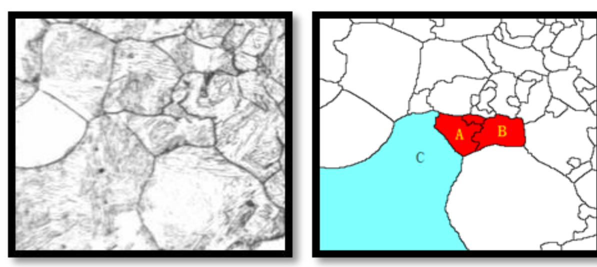
$$\beta = \left(\frac{\beta_0}{P(b_r \mid 0)} \right)^{1/N} \qquad (12)$$

where N is the maximum number of iterations, and $P(b_r \mid N) = \beta_0$.

In order to prevent omitting any of the real-blobs, once a new blob is generated after merging a pseudo-blob, it has to be examined whether it is a real-blob. All identified real-blobs are recorded and used in the pseudo-blobs merge rule.

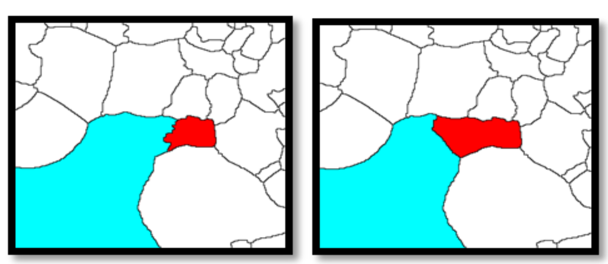
3.2 Revised Pseudo-blob Merge Rule

The new real-blob after identified will be protected and can no more merge other blob during the merge process. As a result, the original pseudo-blob merge rule is revised as follow:
(1) Label the pixels inside pseudo-blobs as blank.
(2) Re-watershed the blank in the image to let the surrounding blobs encroach the pseudo-blob pixels.
(3) Count the pixels encroached by the surrounding blobs and compute the rate. The surrounding non-real-blob with the biggest rate will be the winner. If the surrounding blobs are all real-blobs, the real-blob with the least prior probability will be the winner.
(4) Assign the winner's label to all pseudo-blob pixels.



(a) (b)

Fig. 4. Before Combining the Pseudo-blobs (a) Original image (b) one step before a combination of pseudo-blobs



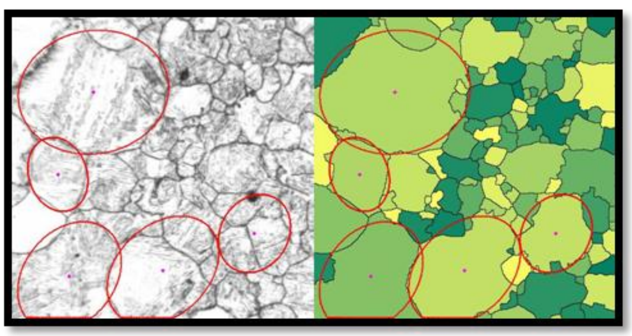
(a) (b)

Fig.5. The Different results of TIWSA and IIWSA After Combining the Pseudo-blobs (a) Result of TIWSA (b) Result of IIWSA

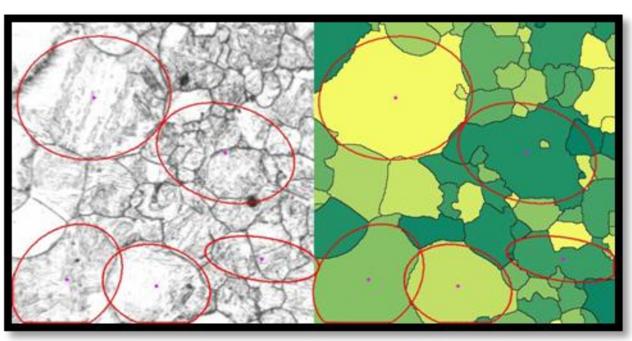
3.3. New Rules in Application

Fig. 4 shows a result of new rule in application of metallographic image segmentation. Fig. 4 (b) is one step during the iterative watershed segmentation of a metallographic image which is shown in Fig.4 (a). Compared with original photograph, the red pseudo-blob A in Fig. 4(b) should be merged to the red blob B. The blue blob C has been a real-blob. However, C in the original photograph has numerous textures which make C much easier than B to encroach the pseudo-blob A. Hence after the re-watershed, as shown in Fig. 5(b), C, instead of B, is the winner and merges the blob A as it occupies the biggest rate of A.

Then we add the real-blob classification rule ($P(b_r \mid N) = \beta_0 = 0.8$) to prevent real-blob C from combining the pseudo-blob A. As the result shown in Fig. 5 (b), blob B merges the blob A and forms a new real-blob leaving real-blob C unchanged. The result shows that once the real-blobs are formed, they can remain unchanged during the merge process. Hence, the prior probability of pseudo-blob can be raised to merge more pseudo-blobs caused by over-segmentation dilemma.



(a)



(b)

Fig. 6. The Comparison of the Results in Application Using TIWSA and IIWSA (a) Result using TIWSA (b) Result using IIWSA

IV. RESULTS AND ANALYZES

This section shows the comparison of the results between TIWSA and IIWSA. Fig. 6 (a) is the result of TIWSA($P(b_p \mid N) = \alpha_0 = 0.4$, $P(b_p \mid 0) = 0.1$) comparing with the result of IIWSA ($P(b_p \mid N) = \alpha_0 = 0.62$, $P(b_p \mid 0) = 0.1$, $P(b_r \mid N) = \beta_0 = 0.68$) in Fig. 6 (b). Evidently, the IIWSA offers a more precise segmentation result than TIWSA, in which more pseudo-blobs become new real-blobs and the real-blobs remain correct after they are formed.

Fig. 7 and Fig. 8 are the results comparing with the original images of other metallographic images using IIWSA. Although these metallographic images have poor quality with disconnected boundaries and heterogeneous intensity which still affect the result of segmentation, most blobs are well segmented according to the original images. In addition, every blob is modeled as ellipse [1] with parameters, for instance, centroid, major/minor axis, orientation, and so on. And 5 blobs which have largest area are marked with red ellipses on both original and segmented image for highlighting.

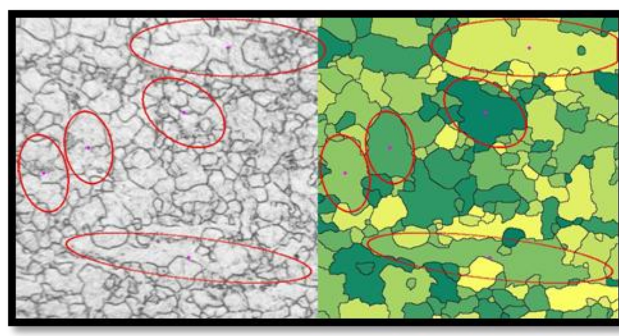


Fig. 7. An Application in Another Metallographic Image (1)

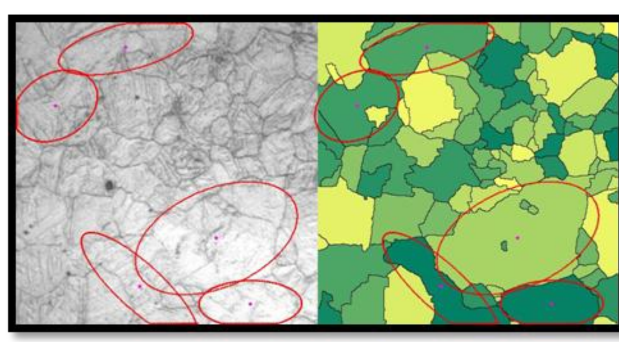


Fig. 8. An Application in Another Metallographic Image (2)

V. CONCLUSION

This paper proposes a revised image segmentation algorithm that mitigates the over-segmentation dilemma of traditional iterative watershed segmentation algorithm by adding a real-blob classification rule and revising the pseudo-blob merge rule. The method can handle complex objects with irregular shapes, disconnected boundaries and heterogeneous intensity. The computational cost is relatively a bit high compared with TIWSA. However, it offers a more satisfactory result. This revised algorithm can be efficiently used not only in metallographic images, but also in other areas, such as medical applications.

Further research will be conducted by adding new processes and principles to tackle more texture disturbance and optimizing the algorithm in order to diminish the computational cost. To inspire further studies on this potential field, the source code could be downloaded freely from Matlab Central.

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