A Watershed Segmentation Algorithm Based on Ridge Detection and Rapid Region Merging

Yan Chen
School of Computer Science and Technology,
Wuhan University of Science and Technology,
Wuhan, China
Hubei Province Key Laboratory of Intelligent Information Processing and Real-time Industrial System,
Wuhan, China
chenyan6106@163.com

Jianxun Chen
School of Computer Science and Technology,
Wuhan University of Science and Technology,
Wuhan, China
Hubei Province Key Laboratory of Intelligent Information Processing and Real-time Industrial System,
Wuhan, China
cjxwh@wust.edu.cn

Abstract—**Due to the effects of noise, quantization error and regional texture details, traditional watershed algorithm tended to lead to over-segmentation. Especially, when the ridges of image are of discontinuity and the edges are of fuzziness, the over-segmentation is significantly worse and the blob of image is easy to lose vital boundary. In this paper, in order to solve these drawbacks, a watershed segmentation algorithm based on ridge detection and rapid region merging was proposed. This algorithm reconstructed discontinuity ridge using ridge historical information which has reserved the information of image segmentation after opening and closing operation and completed pseudo-blobs marks based on Bayes rule, and achieved the mergence and elimination pseudo-blobs by the way of the rapid merging of the maximum similar region. Test results showed that the new image segmentation algorithm could solve the problems of over-segmentation and under-segmentation to the greatest extent, which could greatly increase the accuracy of segmentation of metallographic microgram.**

***Index Terms*—watershed, over-segmentation, reconstructed discontinuity ridge, rapid region merging.**

I. INTRODUCTION

Watershed algorithm was a kind of image segmentation algorithm based on mathematics morphology, which often took an image as a topological relief map and in which the gray value was corresponding to the altitudes, high gray value to peak and low gray value to valley. The lowest basin enlarged its scope by merging the adjacent pixels, finally interpreting the image as various regions consisting by different basins and watersheds, thus could realize the image segmentation. Presently, the commonly used two watershed algorithms were as follows: one was Rapid Watershed Algorithm (RWA) based on immersion simulations proposed by Vincent L et al. [1] in 1991, and the other was Watershed Segmentation Algorithm (WSA) to stimulate rainfall proposed by Smet P. D. et al. [2] in 2000.

The traditional watershed algorithm tended to lead to over-segmentation and it was easy to lose vital boundary to adopt the watershed algorithm in low contrast images. In this paper, non-real module generated by over-segmentation was defined as pseudo-blob. In order to resolve this defects, a lot of related researches were conducted by many scholars, e.g., Tolosa SC et al.[3] realized effective segmentation to nuclear fuel pellet grains using random distribution method; Chen Li et al.[4] conducted the segmentation to metallographic images using the algorithm base on ridge detection and iterative watershed; Yuan Y.T. et al.[5] realized the auto segmentation to sticky approximate circular target using the water growth method base on mathematical morphology; Li X.C. et al.[6] conducted the segmentation to sticky grains using watershed algorithm based on mathematical morphology; Liu J.B. et al.[7] improved the algorithm based on ridge and iterative watershed (hereafter referred to as Traditional Algorithm). The method discussed above made some achievements for the segmentation of metallographic image, however it had some defects. For example, some methods performed poor discontinuous effects of grain boundary segmentation; some possessed defects by ridge detection, which could not eliminate the pseudo-blobs generated by over-segmentation to the greatest extent.

Therefore, in this paper, a watershed segmentation algorithm based on ridge detection and rapid region merging (hereafter referred to as New Algorithm) was proposed to resolve the defects. Moreover, it made an experimental comparison using silicon steel images, and proved that this algorithm could achieve good segmentation results.

II. THE WATERSHED SEGMENTATION ALGORITHM BASED ON RIDGE DETECTION AND RAPID REGION MERGING

Figure 1 displayed the whole process of New Algorithm. In the following sections, the two methods of ridge closed algorithm based on historical information and maximum similar region rapid merging would be discussed in details, i.e. the core algorithm in this paper.

978-1-4799-5274-8/14/$31.00 ©2014 IEEE

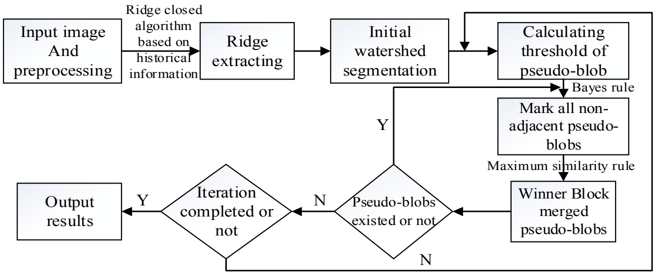


Figure1. Flow chart of the New Algorithm

A. Ridge closed algorithm based on historical information

As the highest waterline in first watershed segmentation, ridge assisted the image segmentation, which was important basis [8, 9, and 10] in judging pseudo-blobs. In mathematics, ridge was defined as extreme point in the direction of maximum curvature, and the ridge distribution image could be obtained by calculating the eigenvalue of HESSIAN Matrix. However, because the lines of initial ridge image were not distinct, and a lot of noise existed, simple region-open might damage the continuity of image profile [11], thus affecting the later segmentation effects. Therefore, ridge closed algorithm based on historical information was proposed to reconstruct the processed ridge image, which was to make ridge more continuous and complete, thus improving the segmentation accuracy.

- Description of ridge closed algorithm based on historical information

This algorithm firstly extracted the original ridge using HESSIAN Matrix, and eliminated the microgroove and noise using the expansive operation of open region and morphology. Finally the algorithm reconstructed ridge using the method of ridge closed, making it to be a closed and continuous ridge image.

1) Judgment of ridge terminal

Define ridge point R_a as the point in $a=(i,j)$ of ridge, and traverse all the pixels in 8-neiborhood of ridge points in sequence. If and only if 8-neiborhood of the ridge point R_a had one and only one ridge point $R_{b=(\mathrm{m,n})}$, the ridge R_a was considered as ridge terminal. To simplify calculation, the binary ridge description was adopted here:

$$R_a=\begin{cases}1 & a=\text{ridge}\\ 0 & a\neq\text{ridge}\end{cases} \qquad (1)$$

2) Method of Ridge closed

To eliminate the microgroove noise in original ridge image, part ridge information was deleted by the morphology and region open operation in Traditional Algorithm, in which finely ridge might exist. In order to maintain the original features in the extended part, the lost boundary needed to be compensated according to historical information. And the steps in judging the boundary were as follows:

a) Traverse all the deleted ridge points, and if R_a was considered as ridge terminal, a new ridge point R_s was generated in point $s=(2i-m,2j-n)$.

b) Extend the ridge point R_a to the new ridge point R_s, repeat the operation of Judgment and Extension, and calculate and accumulate distances $Accum$ from every extended point to the around deleted endpoints. If $Accum$ was less than distance threshold, then the deleted ridge was the boundary; and if $Accum$ was larger than distance threshold, then the invalid ridge should be deleted.

After compensating the deleted boundary information, the ridge image lacking of continuity still needed to use the method of ridge closed algorithm based on historical information to reconstruct the ridge until all ridge points were not the ridge terminals, and finally the reconstruction ended. Here, the new ridge point R_s Equation was described as follows:

Definition R_N was neighborhood set, R_{N_8} was 8-neighbohood set, and in 8-neighbohood, it had one and only one ridge point $R_{b=(\mathrm{m,n})}$. If and only if $\sum R_{N_8}=1$, it could be obtained:

$$R_s=\begin{cases}1 & \sum R_{N_8}=1\\ 0 & \sum R_{N_8}\neq 1\end{cases} \qquad (2)$$

Attention: If it did not meet other ridges after extending a ridge of several pixels for infinite times, the extended part would lose the linear characteristics of the original ridges. Therefore, in the process of extending, reliability demonstration should be conducted for the extended part of ridge. Because the metallographic images were closely continuous, if the extended part of ridge terminal exceeded the extended threshold V_{ridge}, which however could not meet any other ridge terminals, then it proved that the extended part was invalid, which needed to be deleted and kept the same as the original one. As shown in Figure 2, it made a brief summary to the realization idea of the algorithm of extended ridge closed algorithm based on historical information.

0	0	0	0	0	0	0	0	1
0	1	0	0	1	0	0	1	0
1	0	0	0	0	1	0	0	0
0	0	0	0	0	0	0	0	0
0	1	0	0	0	0	0	1	0
0	0	1	0	0	0	0	0	1
0	0	0	0	0	0	0	0	0
0	1	0	0	1	0	0	1	0
1	0	0	0	0	1	1	0	0

0	0	1	1	0	0	0	0	1
0	1	0	0	1	0	0	1	0
1	0	0	0	0	1	1	0	0
1	0	0	0	0	0	1	0	0
0	1	0	0	0	0	0	1	0
0	0	1	0	0	0	0	0	1
0	0	1	1	0	0	0	0	1
0	1	0	0	1	0	0	1	0
1	0	0	0	0	1	1	0	0

0	0	1	1	0	0	0	0	1
0	1	0	0	1	0	0	1	0
1	0	0	0	0	1	1	0	0
1	0	0	0	0	0	1	0	0
0	1	0	0	0	0	0	1	0
0	0	1	0	0	0	0	0	1
0	0	1	1	0	0	0	0	1
0	1	0	0	1	0	0	1	0
1	0	0	0	0	1	1	0	0

Figure2. (a) (b) (c)

where, in Figure 2 (a), the blue region denoted ridge point; in Figure 2 (b), the additive content was the new generated ridge points in "1" region; Figure 2 (c) was the reconstructed ridge sketch image by the method of ridge closed algorithm based on historical information, and as shown in Figure 2 (c), this algorithm could reconstruct the ridges to the continuous ridge images.

- Detection results of the method of ridge closed algorithm based on historical information

As shown in Figure 3, it could be found that the reconstructed ridge image was more complete and continuous using the method of ridge closed algorithm based on historical information. Moreover, in later experimental results, it could be shown that the improved ridge image could perform a better segmentation effect.

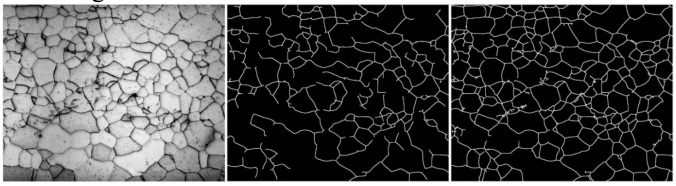


Figure3. (a) (b) (c)
Figure3(a) Metallographic image; (b) Result of Traditional Algorithm; (c) Result by the method of ridge closed algorithm based on historical information

B. *The marking and merging of pseudo-blobs*

To enhance a further accuracy of segmentation and eliminate over-segmentation, two rules were applied in this paper. One was pseudo-blob decision rule which judged the pseudo-blob generated by over-segmentation using Bayesian Classification [4], and the other was pseudo-blob merging rule which merged all pseudo-blobs using the method of the maximum similar region rapid merging.

- Pseudo-blob decision rule

Define V_s as feature vector in the pixel $s=(\mathrm{x},\mathrm{y})$ at time *t*, *t* as iteration, $P(\mathrm{r}_i\,|\,t)$ as prior probability of pseudo-blob r_1 or real-blob r_2 at time *t*. According to Bayesian Classification, posterior probability of pseudo-blob r_1 or real-blob r_2 in V_s was as follows:

$$P(\mathrm{r}_i\,|\,V_s,t)=\frac{P(V_s\,|\,\mathrm{r}_i,t)P(\mathrm{r}_i\,|\,t)}{P(V_s\,|\,t)},i=1,2 \tag{3}$$

According to Bayesian Classification, the pixel in pseudo-blob satisfied the following formula:

$$P(\mathrm{r}_1\,|\,V_s,t)>P(\mathrm{r}_2\,|\,V_s,t) \tag{4}$$

If the feature vector V_s in s came from pseudo-blob or real-blob, it satisfied the following formula:

$$P(V_s\,|\,t)=P(V_s\,|\,\mathrm{r}_1,t)\times P(\mathrm{r}_1\,|\,t)+P(V_s\,|\,\mathrm{r}_2,t)\times P(\mathrm{r}_2\,|\,t) \tag{5}$$

Substitute all pixels in pseudo-blob into calculation and substitute Equation (3) and (5) into (4), it could be obtained:

$$2P(r_1\,|\,t)>\frac{\sum_{s\in r_i}P(V_s\,|\,t)}{\sum_{s\in r_i}P(V_s\,|\,r_1,t)} \tag{6}$$

In t^{th} iteration, the prior probability of pseudo-blob could be written as the following recursion:

$$P(r_1\,|\,t)=\alpha P(r_1\,|\,t-1)\,,\alpha=\left(\frac{\alpha_0}{P(r_1\,|\,0)}\right)^{1/N} \tag{7}$$

where, N was the maximum iteration, and $P(r_1\,|\,N)=\alpha_0$ was the prior probability of the last iteration.

In summary, the prior probability of pseudo-blob was taken as decision threshold to judge the proportion of ridge information in each segmented block boundary was less than the prior probability of pseudo-blob, which indicated the importance of complete ridge information. If it was less than this decision threshold, then it was considered that the segmentation block was the pseudo-blob generated in over-segmentation. In each iteration process, most pseudo-blobs could be found out by enlarging the decision threshold of pseudo-blob using recurrence formula.

- Rapid merging of the maximum similar region

After initial watershed segmentation, because the internal grey level of every image subset (reception basin) possessed homogeneous features, it was necessary to merge every image subset, improve region fuzziness, and finally form significant regions [12]. In this paper, the method of the maximum similar region rapid merging was proposed to merge pseudo-blobs.

1) Description of this algorithm

As shown in Figure 4, if Region A was the marked pseudo-blob, calculate the similarities of Region A and the neighbored Region B, C, D and sort the orders of the similarities. The one which had the most similarity was marked as Winner Block P, and finally the pseudo-blob was completely merged by Winner Block P.

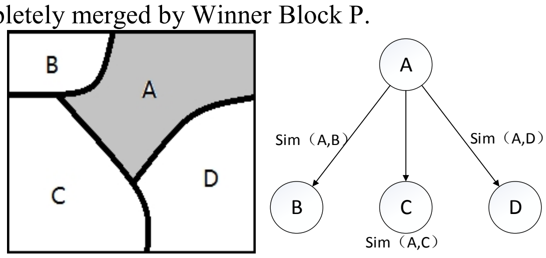


Figure4. Merging principle schematic of the maximum similarity region

$Sim(\mathrm{A},\mathrm{P})=\mathrm{MAX}\{\mathrm{Sim}(\mathrm{A},\mathrm{B}),\mathrm{Sim}(\mathrm{A},\mathrm{C}),\mathrm{Sim}(\mathrm{A},\mathrm{D})\}$ Winner Block P completely merged Pseudo-blob A.

2) Calculating rule of similarity

Define $G(i,j)$, $E(i,j)$ and $A(i,j)$ as the gray level contrasts of Region i and Region j, and the ridge similarity and region adjacency relationship were as follows:

$$G(i,j)=\frac{R_i\cdot R_j}{R_i+R_j}\left(\mu_i-\mu_j\right)^2 \tag{8}$$

$$A(i,j)=\begin{cases}1 & i \text{ and } j \text{ are adjacent}\\ \infty & i \text{ and } j \text{ are not adjacent}\end{cases} \tag{9}$$

$$E(i,j)=\frac{|\eta_i-\eta_j|+1}{\sigma_i+\sigma_j+1} \tag{10}$$

In Formula (8), R_i and R_j indicated the pixel numbers in Region i and Region j ; μ_i and μ_j indicated the gray averages in the two regions. In Formula (10), σ_i and σ_j indicated the gray averages of the pixels of region boundary on both sides of the ridge; η_i and η_j indicated the gray variances of the pixels of region boundary on both sides of the ridge. If ridge was the typical boundary, the pixel gray levels on both sides of it would display a significant change, and then $|\eta_i - \eta_j|$ would become larger, σ_i and σ_j become smaller. In addition, adding 1 to numerator and denominator respectively was to avoid $|\eta_i - \eta_j|$, and if one of $\sigma_i+\sigma_j$ was judged to be 0, the other judgment could still work.

Define $Sim(i,j)$ as the similarity between Region i and Region j, and then similarity formula was as follows:

$$Sim(i,j)=\frac{1}{G(i,j)\cdot E(i,j)\cdot A(i,j)+1} \tag{11}$$

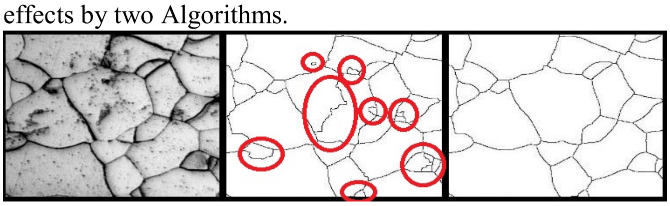
Attention: Here only the similarity was between the marked pseudo-blobs and neighborhood regions, therefore, Region i and Region j were adjacent regions, i.e., $A(i,j)=1$ and $Sim(i,\mathrm{j})$ could be simplified as:

$$Sim(i,j)=\frac{1}{G(i,j)\cdot E(i,j)\cdot A(i,j)} \tag{12}$$

III. EXPERIMENT AND ANALYSIS

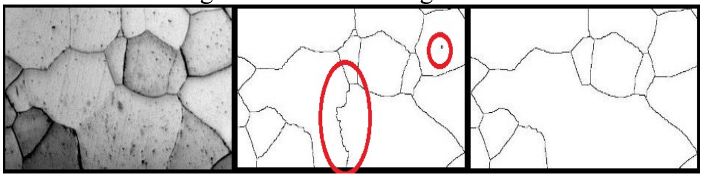
A. Experimental results

In the experiment, segmentations of different metallographic images were conducted by Traditional Algorithm and New Algorithm. In the following, local segmentation comparison and complete segmentation comparison were applied to comparing the segmentation effects by two Algorithms.



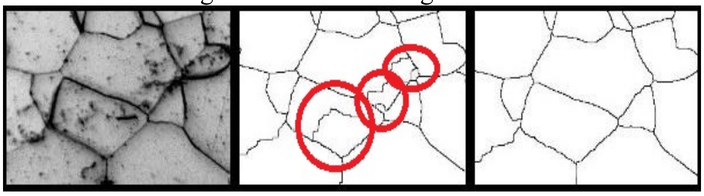
(a) (b) (c)

Figure5. Local segmentation comparisons of Traditional Algorithm and New Algorithm



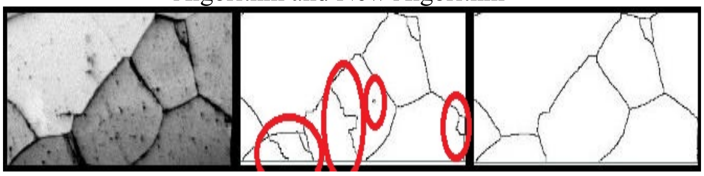
(a) (b) (c)

Figure6. Local segmentation comparisons of Traditional Algorithm and New Algorithm



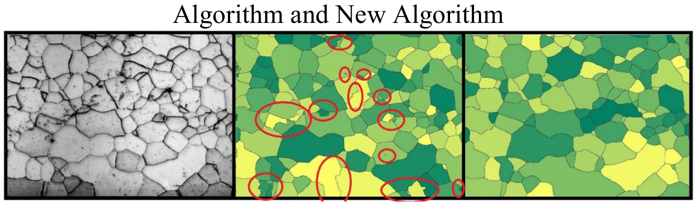
(a) (b) (c)

Figure7. Local segmentation comparisons of Traditional Algorithm and New Algorithm



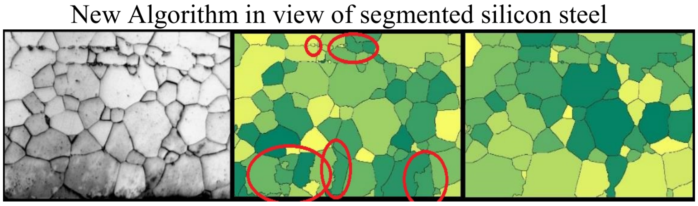
(a) (b) (c)

Figure8. Local segmentation comparisons of Traditional Algorithm and New Algorithm



(a) (b) (c)

Figure9.Complete comparisons of Traditional Algorithm and New Algorithm in view of segmented silicon steel



(a) (b) (c)

Figure10.Complete comparisons of Traditional Algorithm and New Algorithm in view of segmented silicon steel

Figure 5, 6, 7, 8, 9 and 10 indicated the local segmentation comparisons of metallographic images with two algorithms, while Figure 9, 10 indicated the complete comparisons of different metallographic images, in which (a) was the original metallographic image; (b) was the segmentation results by Traditional Algorithm; and (c) was the segmentation results by New Algorithm. Here, red circle represented the pseudo-blobs generated by over-segmentation in Traditional Algorithm.

B. Result analysis

To make a direct effect comparison of Traditional Algorithm and New Algorithm, experimentation method was adopted to evaluate the two segmentations effects in this paper

[13]. The reference image was the manual segmentation result image, and in this paper, over-segmentation ratio and under-segmentation ratio were taken as evaluation indexes of experimentation method:

1) Over-segmentation ratio

$$OSR = \prod_{i,j} \frac{card(\mathrm{S}_i \cap R_j)}{card(\mathrm{R}_j)}, card(\mathrm{S}_i \cap R_j) \neq 0 \quad (13)$$

R_j was a region in reference image, and in segmentation image, this region was segmented as $S_1 \cup S_2 \cup S_3 \Lambda S_q$. If OSR value was 1, then over-segmentation did not exist in segmentation algorithm. If the value was much less than 1, it indicated a bad over-segmentation.

2) Under-segmentation ratio

$$USR = \prod_{i,j} \frac{card(\mathrm{S}_j \cap R_i)}{card(\mathrm{S}_j)}, card(\mathrm{S}_j \cap R_i) \neq 0 \quad (14)$$

S_j was a region in segmentation image, and in reference image, this region consisted of $R_1 \cup R_2 \cup R_3 \Lambda R_q$. If USR value was 1, then under-segmentation did not exist in this segmentation algorithm. If the value was much less than 1, it indicated a bad under-segmentation.

Table 1 Results comparison of Traditional Algorithm and New Algorithm

Test image	Evaluation indexes	Traditional Algorithm	New Algorithm	%Improved
Figure 9	OSR	0.63125	0.96791	%24.45
	USR	0.65648	089756	%26.86
Figure 10	OSR	0.69125	0.90882	%23.93
	USR	0.68823	0.89852	%23.40

As shown in above Table 1, it could be found out that the New Algorithm proposed in this paper solved partly the problems of over-segmentation and under-segmentation, which improved the segmentation accuracy.

IV. CONCLUSION

In order to solve defects of traditional watershed algorithm, a watershed segmentation algorithm based on ridge detection and rapid region merging was proposed in this paper. The core of this algorithm was the methods of ridge closed algorithm based on historical information and the maximum similarity region rapid merging. Using the method of ridge closed algorithm based on historical information to reconstruct continuous lacking ridge images was beneficial to marking the later pseudo-blobs to the greatest extent, while using the method of the maximum similarity region rapid merging could merge pseudo-blobs rapidly, and additionally it possessed good merging accuracy and high executive efficiency. Finally, by representing the result comparisons of the two algorithms, it proved that New Algorithm could solve the problems of over-segmentation and under-segmentation to the great extent thus greatly increasing the segmentation accuracy of metallographic images.

ACKNOWLEDGMENT

This work was supported by the National Natural Science Foundation of China (Grant Nos. 31201121 and 61100055).

REFERENCES

[1] Vincent L, Soille P. Watershedsin Digital Spaces: An Efficient Algorithm Based on Immersion Simulations [J]. IEEE Transactions on Pattern Analysis and Machine Intelligence, 1991, 13(6): 583-598.

[2] SMET P D, PIRES RL, Implementation and analysis of an optimized rain falling Watershed algorithm [J] .SPIE Image and Video Communications and Processing, 2000,3974:759-766.

[3] TOLOSA S, BLACHER S, DENIS A. Two methods of random seed generation to avoid over segmentation with stochastic watershed: application to nuclear fuel micrographs [J].Journal of Microscopy-ox ford, 2009, (01):79-86.

[4] Li Chen, Min Jiang, Jianxun Chen. Image Segmentation Using Iterative Watersheding Plus Ridge Detection. In: 2009 IEEE International Conference on Image Processing, Egypt: 2009.

[5] YUAN T Y, JIANG ZH G, MENG R .Automatic splitting and separating overlapped object in target-segmented image [J]. Chinese Journal of Stereology and Image Analysis, 2003, 8(1):4043.

[6] Li X.C., Wang Y.P., Zhu X.W. Metallurgical microstructure image restoration method based on morphology [J].Computer Engineering and Design, 2008, (14):3807-3809.

[7] Liu J.B., Chen J.X. An Improved Iterative Watershed According to Ridge Detection for Segmentation of Metallographic Image [J]. American Journal of Science and Engineering, Vol. 1, No. 1, 2012.

[8] Luo J., Zhang W.X., Acquisition of Fingerprint Angle Feature Based on Ridge Line Tracking [J].Journal of Shanghai University, 2002, 8(2): 105-111.

[9] Liu W., Liu G.B., Mao R.H. An Improved Method of Ridge Line Extraction [J]. Modern Radar, 2004, 26(7): 31-40.

[10] Tony Lindeberg. Edge Detection and Ridge Detection with Automatic Scale Selection. International Journal of Computer Vision, 1998, 2: 117-156.

[11] Jiang M.X, Chen G.H. Restoration and reconstruction of grain boundary in metallographic image [J].Optics and Precision Engineering, 2011,19(10): 2541-2549.

[12] Yang H.F. An Image Segmentation Method Based on Improved Watershed Algorithm and Region Merging [J].Microcomputer Applications, 2008, 28(11): 1132-1137.

[13] Ding L., Zhang Y.P.et al. A Survey of Image segmentation Techniques and Performance Evaluation [J].Software, 2010, 31(12): 78-83.