# IMAGE SEGMENTATION USING ITERATIVE WATERSHEDING PLUS RIDGE DETECTION

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**ABSTRACT**

This paper presents a novel segmentation algorithm for metallographic images, especially those objects without regular boundaries and homogeneous intensities. In metallographic quantification, the complex microstructures make conventional approaches hard to achieve a satisfactory partition. We formulate the segmentation procedure as a new framework of iterative watershed region growing constrained by the ridge information. The seeds are selected by an effective double-threshold approach, and the ridges are superimposed as the highest waterlines in the watershed transform. To tackle the over-segmentation problem, the blobs are merged iteratively with the utilization of Bayes classification rule. Experimental results show that the algorithm is effective in performing segmentation without too much parameter tuning.

**Index Terms —** Image analysis, image segmentation, morphological operations

## 1. INTRODUCTION

Image segmentation refers to the process of partitioning a digital image into multiple regions. Each of the pixels in a region is similar with respect to some characteristics, such as intensity, gradient, or texture. Adjacent regions are significantly different with respect to the same characteristics. The goal of segmentation is to simplify and change the representation of an image into objects that are more meaningful and easier to analyze [1].

In image processing literature, the segmentation is well-studied and can be classified into several categories [1]-[3]. Threshold-based methods are very effective for images containing solid objects in a contrasting background. In this technique, the peaks and valleys in the histogram are typically used to locate the threshold in the image. It is computational efficient and easy to implement. Edge-based methods are a well-developed field on its own within image processing. Since there is often a contrast in intensity between the object and background, the detected edges can be used to trace the object boundaries. However, the edges identified are often disconnected, while one needs closed region boundaries to segment an object. The clustering methods, e.g. the K-means algorithm, choose cluster centers and assign each pixel in the image to the cluster that minimizes the variance between the pixel and the center. Region growing methods are worked based on the seed growing principle. The regions are iteratively expanded by comparing all unallocated neighboring pixels to the regions. In medical segmentation, active contour and levelset methods are effective for tracking interface and shape of a tissue, e.g. mammogram [4]. In many real-world applications, however, several aforementioned techniques need to combine together to yield a satisfactory partition.

This paper presents a novel segmentation algorithm to handle the real-life metallographic images. The matlab source code is available online for research purpose [5]. In such applications, objects have severely irregular shape with inhomogeneous intensities. This makes the conventional approaches hard to achieve a reasonable segmentation. In view of this, we formulate the segmentation procedure as a new framework of iterative watershed region growing constrained by the ridge information. The seeds are selected by an effective double-threshold approach, and the ridges are superimposed as the highest waterlines in the watershed transform. To tackle the over-segmentation problem, the blobs are merged iteratively with the utilization of Bayes classification rule. Experimental results show that the new algorithm is effective in performing segmentation without too much parameter tuning.

## 2. PROBLEM SPECIFICATION

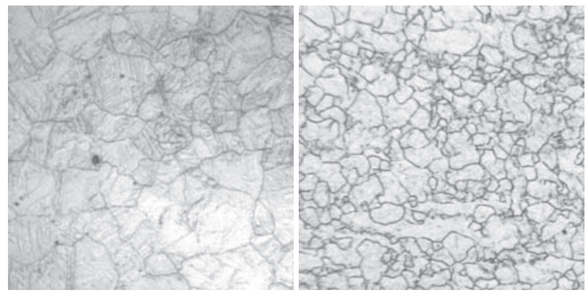
Metallography is the science of preparing a metal surface for analysis by grinding, polishing, and etching to reveal microstructual constituents. Metallographic image analysis is essential for objectively assessing the material properties with its microstructure. Microstructure quantification is performed by examining the metallographic specimens under suitable electronic/optical instruments and the image obtained. The technique is valuable in the research and production of all metals and alloys and non-metallic or composite materials.

In this work, a blob is used to denote a group of pixels making up a microstructure. As shown in Figure 1, the connected pixels with similar gray intensity and black boundary can be thought of as blob. Features of blob, including size, shape, curvature, orientation, and distribution, could serve as criterion for quality assessment. In order to perform image analysis automatically, the first step is to segment each microstructure. However, conventional image segmentation techniques are unsuitable to achieve the goals due to several reasons.

Firstly, each microstructure has irregular shape. It is unlike the blood red cell, which can be modeled as circle and detected via Hough transform. The size of each microstructure is quite different from each other. Some may be 10 times larger than the tiny one. Secondly, the pixel intensities inside each blob are inhomogeneous due to tissues texture properties. The image quality is further degraded by uneven illumination and noise disturbance during image capturing process, as shown in Figure 1(a). All these make the threshold-based approaches hard to achieve a satisfactory partition. Thirdly, boundary is not always a useful indicator to separate blob. As show in Figure 1(b), a lot of microstructures are connected without a definite closed-boundary. At the same time, the boundary tips extend into the interior of some blobs randomly. Even there is a sharp contrast in intensity at the region boundaries, the edge-based segmentation cannot be used alone to achieve our goal.

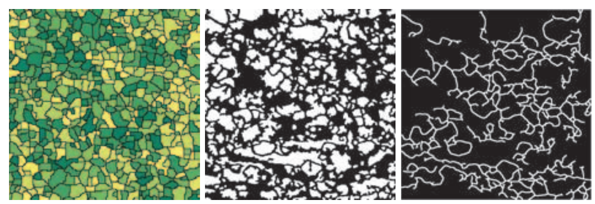
Watershed transform is one of the classical and effective methods in the field of segmentation [6]. In mathematical morphology, it considers the magnitude of an image as a topographic surface. The lowest basins expand their territory gradually by incorporating neighboring pixels with similar values, thus form a set of regions that collectively cover the entire image. In practice, conventional watershed transformation typically produces over-segmentation due to numerous local minima and irregularities existing in real images. An over-segmentation example for Figure 1(b) is shown in Figure 2(a). One possible enhancement is to define a set of markers to mark those regions that require segmentation [7]. Nevertheless, it is generally difficult to obtain relevant markers automatically without any interaction by the user.

In this work, we extend the marker-controlled watershed transformation in three aspects. (i) The controlled markers consist of seeds and boundaries. The seeds are selected by an effective double-threshold approach, and the boundaries via ridge detection rather than edge detection. (ii) Bypassing the time-consuming "edge-linking" step, the detected boundaries need not to be closed. Therefore, it is not required that a seed should correspond to one closed-boundary. (iii) The over-segmentation dilemma is remedied via an iterative classification and merging procedure.



(a) (b)

Figure 1. Sample metallographic images.



(a) (b) (c)

Figure 2. The test on a metallographic image. (a) Over-segmentation by watershed, (b) Seed detection by double-threshold, (c) Under-detection results by scale-space ridge detection.

## 3. PROPOSED SCHEME

### 3.1. Seed detection

The watershed transform takes a set of seeds for region growing. The seeds work as the lowest basins and mark each of the initial objects to be segmented. Since the main body of a microstructure is intensity brighter than the dark boundary in nature. The seeds could be automatically chosen by a simple double-threshold approach.

Let $T_G$ and $T_A$ stand for the pixel intensity threshold and blob area threshold, respectively. At first, the morphological extended-maxima transform with $T_G$ are used to find the regional connected components [8]. As a result, we get a binary image. Next, blob less than $T_A$ in area is removed. A seed detection example for Figure 1(b) is shown in Figure 2(b). In this work, $T_G = 0.1$ for gray level [0, 1] and $T_A = 20$ pixels.

### 3.2. Ridge detection

In metallographic images, the boundaries are relatively salient and robust in the cluttered microstructures. Fortunately, it is observed that all the boundaries in an image always have constant intensity (dark) and width characteristics. This provides key information when segmenting blobs. As stated previously, the edge detection/linking approach will not be favored because of the irregular shape and discontinuity.

Inspired by the success of ridge detector in fingerprint and vessel analysis [9], [10], we start our boundary extraction task with a short review of ridge descriptors. Mathematically, the ridge is defined as the local extreme point in the direction of the largest surface curvature, and can be detected by computing the eigenvalue of the Hessian matrix [11]. It is noted that the fixed-scale ridge definition can be very sensitive to the different object width. The notion of *scale-space ridges* had been introduced in [12]. It allows the scale parameter to be automatically tuned to the width of the ridge structures in the image domain. The ridge detection method used in this work is described in full detail in [12]. As shown in Figure 2(c), the detected ridges are marked by white pixels.

It is worth mentioning that even the ridge descriptor works well at indicating boundaries with different widths and orientations, the detector still yields false/missing detections. In this work, we choose to minimize the false detection error (i.e. Type II error). Because watershed transform always have an over-segmentation result, an under-detection result for ridge detection is preferred.

### 3.3. Iterative scheme

The first time watershed transform is performed after superimposing the ridge as the highest waterline, and the seed marker as the lowest water-basin on the original image. Even above strategy can increase the segmentation accuracy up to a level, there are still some over-segmentation existed.

In order to improve the accuracy further, an iterative scheme is proposed with two main steps, i.e. pseudo-blob classification rule and pseudo-blob merge rule. The first step is to decide which blob is the over-segmented one, named as pseudo-blob. The second step is to reallocate the pixels of a pseudo-blob into other real-blobs.

*(a) Pseudo-blob classification rule*

Let $v_s$ be a 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 $b_1$ or real-blob $b_2$ is given by

$$P(b_i \mid v_s, t) = \frac{P(v_s \mid b_i, t) P(b_i \mid t)}{P(v_s \mid t)}, \quad i = 1,2 \tag{1}$$

Using the Bayes decision rule, the pixel is classified as inside a pseudo-blob if the feature vector satisfies

$$P(b_1 \mid v_s, t) > P(b_2 \mid v_s, t) \tag{2}$$

Noting that the feature vector $v_s$ associated the pixel $s=(x,y)$ are either from a real-blob or a pseudo-blob, it follows that

$$P(v_s \mid t) = P(v_s \mid b_1, t) P(b_1 \mid t) + P(v_s \mid b_2, t) P(b_2 \mid t) \tag{3}$$

Taking all the pixels in a blob into account, and substituting (1) and (3) to (2), it becomes

$$2P(b_1 \mid t) > \sum_{s \in b_1} P(v_s \mid t) / \sum_{s \in b_1} P(v_s \mid b_1, t) \tag{4}$$

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

$$P(b_1 \mid t) = \alpha P(b_1 \mid t-1) \ \ and \ \ \alpha = \left(\alpha_0 / P(b_1 \mid 0)\right)^{1/N} \tag{5}$$

where $N$ is the maximum number of iterations, making $P(b_1 \mid N) = \alpha_0$ at the final iteration

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

$$P(v_s \mid t) = \begin{cases} 1 & s = ridge \\ 0 & s \neq ridge \end{cases} \tag{6}$$

Experimental results demonstrate that the method achieves a satisfactory segmentation while keeping computational efficient when binary ridge descriptor is chosen as feature.

*(b) Pseudo-blob merge rule*

There are two basic ideas to re-group the pixels inside a pseudo-blob, either pixel-by-pixel or all pixels as a whole. In this work, we found the later always gives reasonable results. If reallocating pixels to different neighboring blobs, it will result in a "splitting" artifact. Therefore, the proposed merge rule is based on "winner-take-all" principle.

(i) Label the pixels inside a pseudo-blob as blank.

(ii) Re-watershed the images to let the surrounding blobs encroach the pseudo-blob pixels.

(iii) Counting the maximum occurrence label of the pseudo-blob pixels.

(iv) Assign the maximum occurrence label to all pseudo-blob pixels.

### 3.4. Overview

The proposed iterative watersheding plus ridge detection algorithm is summarized as follows:

*(I) Initial watershed with the ridge constraint*

*(i) Perform double-threshold seed detection.*

*(ii) Perform scale-space ridge detection.*

*(iii) Superimpose the ridge as the highest waterline, the seed as the lowest water-basin on the original image.*

*(iv) Perform first time watershed transform.*

*(II) Iterative watershed with the Bayes rule*

*(v) Set blob probability and feature probability.*

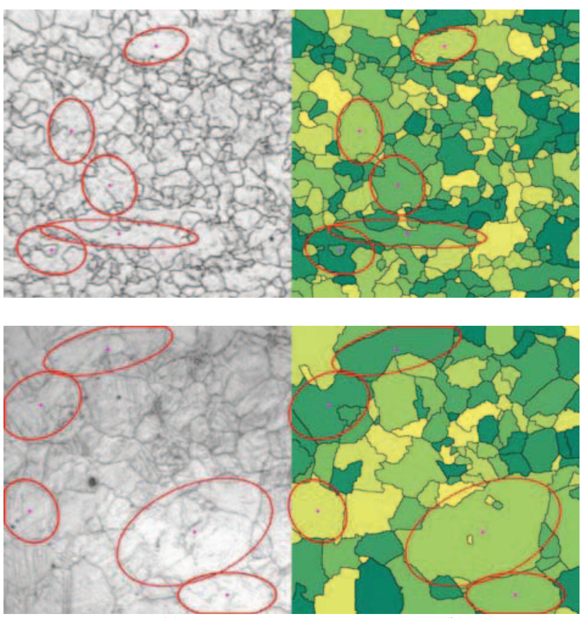
*(vi) Perform Bayes pseudo-blob classification.*

*(vii) Perform "winner-take-all" merge.*

*(viii) Repeat Step (v)-(vii) until no blob needs to be merged or a maximum number of iterations is reached.*

## 4. EXPERIMENTAL RESULTS

The effectiveness of the proposed algorithm is illustrated in this section. The experiment is based on a set of metallographic images. Among them, two samples images are showing in Figure 1. The proposed method is implemented as stated in Section 3 with few parameters, e.g. $T_G = 0.1$ , $T_A = 20$ , $N = 3$ , $P(b_1 | 0) = 0.1$ , $\alpha_0 = 0.6$. The segmented blobs are shown in Figure 3. It is observed most blobs are segmented corrected by comparing the original image in Figure 3(a) and the results Figure 3(b). In addition, each blob is modeled as ellipse with parameters such as centroid, major/minor axis, orientation. The five largest blobs are displayed using red color in the image for visualization. Experiments on the test set with 200 images demonstrate the method is effective in performing segment metallographic images, especially those objects without a regular boundaries and homogeneous intensities. Moreover, the performance of the proposed method is not sensitive to the parameters too much.



(a) (b)

Figure 3. Experimental results. (a) Original image, (b) Blob segmentation.

## 5. CONCLUSION

This paper proposes a novel image segmentation algorithm. We formulate the segmentation procedure as a framework of iterative watershed region growing constrained by the ridge information. The method can handle complex objects without clear boundaries and homogenous intensities. The computational cost is relatively low with a satisfactory result. The proposed method is not only efficient for metallographic images, but also promising in other areas, such as medical applications.

Further investigation will be conducted by adding level set algorithm to tackle more texture disturbance. To inspire further research on this very interesting field, the sourcecode could be downloaded freely from Matlab Central [5].


## ACKNOWLEDGEMENT

This research was supported by National Natural Science Foundation of China under Grant NO. 60705012, partly supported by Science Foundation of Wuhan University of Science and Technology under Project 2008TD04.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