Texture-Based Region Merging for Watershed Segmentation in Sonography

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Abstract

Watershed transformation is one of the most reliable automatic and unsupervised segmentation techniques. However, the watershed transformation always produced over-segmentation for images which comprise noise and irregular textures. In this paper, we propose a new texture-based region merging method for watershed segmentation to solve the over-segmentation problem. The texture information is utilized in our merging process to control over-segmentation. The experimental results show that the proposed texture-based merging method performed well for images that are rife with noise, speckles, and textures.

Keywords: watershed transformation, over-segmentation, textural analysis, image segmentation, sonography

1. Introduction

Image segmentation is an essential procedure in image analysis tasks such as image visualization, description, recognition, and object based compression. Many techniques have been proposed to achieve segmentation and can be classified into three groups: thresholding, edge-based, and region-based methods. Intensity thresholding technique which is the oldest segmentation method is still widely used in some applications since it is computationally inexpensive. An image in the thresholding method is assumed to be composed of several similar intensity objects on the background. However, the number of similar intensity classes is difficult to determine. On the other hand, edge-based methods are based on the assumption of that the abrupt change of intensity in an image corresponds to the boundary between objects. However, the edge detection procedure always produced many false edges. Edge relaxation procedure is needed to obtain the true closed boundaries. Unfortunately, the edge procedure is complicated and very time consuming.

We focus on the studies of region-based segmentation in this paper. One of the most reliable automatic and unsupervised segmentation is the watershed transformation [2], [4], [6], [8]. These segmentation transformation methods have been applied successfully to solve some difficult and diverse image segmentation problem. In 1999, Gauch proposed a sophisticated watershed-based segmentation algorithm [2]. However, the method always produced over-segmentation for images which comprise noise or irregular textures. In order to solve the over-segmentation problem, many morphological operation methods have been proposed in [1], [5], [7]. These approaches have the disadvantage of distorting the location of boundaries and high computational complexity. Hence, we utilize the non-linear medium filter as a preprocessing filter to avoid over-segmentation and preserve the location of boundaries. Moreover, the proposed method merges the most pair of regions according to a similarity function which is based on the texture feature of region. The experimental results showing that the texture-based merging is visually reasonable.

The rest of this paper is organized as follows. Section 2 describes the Gauch's watershed transformation algorithm. Section 3 reviews a traditional region homogeneity merging and depicts the proposed texture feature merging method. In Section 4, we give the experimental results for the clinical ultrasonic images. Finally, conclusions are drawn in Section 5.

2. Watershed Segmentation

Multi-scale gradient watershed hierarchies can be used for automatic or interactive image segmentation. By selecting sub-trees of the region hierarchy, visually sensible objects in an image can be easily constructed. Thus, the Gauch's watershed algorithm is used in the proposed method to produce the initial segments for an image.

Firstly, Gaussian low-pass filtering is utilized to smooth the input image *I*. The spread of the Gaussian filtering was used to construct a watershed hierarchy. A gradient magnitude image (GMI) is defined as:

$$I_{\mathrm{GMI}} = \left\| \nabla \left(g \left(I \right) \right) \right\| . \qquad (1)$$

Local intensity minima (LIM) are then identified in the GMI, where a LIM corresponds to a central pixel whose values is less than all neighbors in a 3 × 3 window. For the remaining pixels, a morphological gradient direction is defined as the direction going from the pixel to its neighbor having the smallest value. Finally, for a non-LIM pixel, the algorithm follows its gradient direction downhill until it reaches a LIM. Then, the starting non-LIM pixel is labeled with the corresponding LIM label. The procedure splits the given GMI into two watershed regions is illustrated in Fig. 1.

3. Region Merging

After applying the Gauch's watershed transformation, a merging procedure is still required to obtain a meaningful segmentation from the initial watershed segmentation. The region adjacency graph (RAG) [3] is used to show the relationship among the segmented regions in an image. Once the RAG is constructed the number of regions can be reduced by merging regions with the smallest similarity metric. The RAG is then updated and the process repeated. This section reviews a traditional merging based on region homogeneity and proposes a new merging method based on texture feature.

3.1. Region homogeneity based merging

A nature criterion for merging regions is the similarity between their intensity levels. If R_K^* is the optimal K-partition with respect to the squared error, then the optimal (K - 1)-partition is obtained by merging the pair of regions in R_K^*, which minimizes the following dissimilarity function:

$$\delta^H\left(R_K^{*i}, R_K^{*j}\right) = \frac{\left\|R_K^{*i}\right\| \cdot \left\|R_K^{*j}\right\|}{\left\|R_K^{*i}\right\| + \left\|R_K^{*j}\right\|}\left[\mu\left(R_K^{*i}\right) - \mu\left(R_K^{*j}\right)\right]^2. \qquad (2)$$

where $\mu\left(R_K^{*i}\right)$ and $\mu\left(R_K^{*j}\right)$ correspond to the mean value of I in the adjacent regions R_K^{*i} and R_K^{*j}, respectively.

Figures 2(a), 4(a), 6(a), 8(a), and 10(a) are the original breast ultrasonic images. Figures 2(b), 4(b), 6(b), 8(b), and 10(b) show the results obtained from using medium filtering and watershed transformation. Figures 2(c), 4(c), 6(c), 8(c), and 10(c) illustrate the merging process based on region homogeneity. Clearly, the final segmentation comprises many false boundaries in breast ultrasonic images.

3.2. Texture-based merging

In this paper, we use a texture description, co-occurrence matrix as criteria to determine whether regions can merge or not. The co-occurrence matrix is based on the repeated occurrence of some gray-level configuration in the texture, this configuration varies rapidly with distance in fine textures and slowly in coarse textures. Suppose the part of a textured image to be analyzed is an $M \times N$ rectangular area. An occurrence of some gray-level configuration may be described by a matrix of relative frequencies $P_{Ø\ d}\,(a,b)$ that describes how the frequency of two pixels a and b appear in the area which separated by a distance d in direction Ø. The texture criteria derived from the following co-occurrence matrices $\boldsymbol{O_1}$, $\boldsymbol{O_2}$, $\boldsymbol{O_3}$, $\boldsymbol{O_4}$, and $\boldsymbol{O_5}$.

Energy:

$$O_1 = \sum_{a,b} P_{\phi,d}^2(a,b), \qquad (3)$$

Entropy:

$$O_2 = \sum_{a,b} P_{\phi,d}(a,b)\log_2 P_{\phi,d}(a,b), \qquad (4)$$

Maximum probability:

$$O_3 = \max_{a,b} P_{\phi,d}(a,b), \qquad (5)$$

Contrast: (a measure of local image variations; typically k = 2 and λ =1)

$$O_4 = \sum_{a,b} |a-b|^k P_{\phi,d}^{\lambda}(a,b), \qquad (6)$$

Inverse difference moment:

$$O_5 = \sum_{a,b;\,a\neq b} \frac{P_{\phi,d}^{\lambda}(a,b)}{|a-b|^k}. \qquad (7)$$

The co-occurrence matrices difference in scale from the texture feature. The statistics must be either normalized or rank ordered to be properly combined the scale of the dissimilarity. In this paper, a weighted matrix F_{weight} for the five co-occurrence matrices is defined as:

$$F_{weight} = \sum_{i=1}^{5} W_i O_i \quad (0 < W \leq 1). \qquad (8)$$

where W_i is the weight factor for each co-occurrence matrix O_i. A predefined threshold is utilized to decide the difference between two regions obtained from weighted matrix. The RAG is used to represent the relation between regions. These two conditions are used to decide whether the two regions can merge or not.

4. Experimental Results

We demonstrate our texture-based region merging method in the ultrasonic image as shown in Figs. 2(a), 4(a), 6(a), 8(a), and 10(a). As previous section, the Gauch's watershed transformation with the non-linear medium filter was used as the initial segmentation procedure.

The simulation results are shown in Figs. 2(b), 4(b), 6(b), 8(b), and 10(b). Then we use traditional merging process based on region homogeneity to obtaine the final segmentation image. The results are shown in Figs. 2(c), 4(c), 6(c), 8 (c) and 10(c). From the experimental results, the traditional merging process based on region homogeneity may get false boundaries in the final segmentation.

In the proposed texture-based region merging method, we set W_2 = 1 firstly, the results show shown in Figs. 3(a), 5(a), 7(a), 9(a), and 11(a) that it's worse than using homogeneity. To improve it, the W of each co-occurrence matrices is set to 0.2 instead. The results are shown in Figs. 3(b), 5(b), 7(b), 9(b), and 11(b). We can find the contour of the tumor is clearer than that of using merging process based on region homogeneity, but there are still some small regions. Afterwards, we try to set W for each co-occurrence matrices. Figures 3(c), 5(c), 7(c), 9(c), and 11(c) are the segmentation results with W_1 = 0.1, W_2 = 0.3, W_3 = 0.2, W_4 = 0.3, and W_5 = 0.1. The proposed method allows the contour of the tumor clearer by merging the tiny regions. From the experimental results, the effective segmentation result in breast tumor image can be obtained by using the proposed texture feature merging method.

5. Conclusion

This paper proposes a method of watershed transformation region merging for gray level image segmentation. The watershed transformation is used to generate the initial segments and the texture information. Additionally, the non-linear preprocessing filtering procedures reduce the over-segmentation efficiently. The RAG technique is used to analyze the relationship between regions.

After that, we utilize the co-occurrence matrices as the adaptable texture features to merge regions in an image. The experimental results show that the proposed method is an effective and useful method in ultrasonic image segmentation.

Acknowledgements

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References

[1] A. N. Evans and M. S. Nixon, "Mode filtering to reduce ultrasound speckle for feature extraction." *IEE Proceedings- Vision, Image and Signal Processing*, vol. 142, Issue: 2, Apr. 1995, pp.87-94.

[2] J. M. Gauch, "Image segmentation and analysis via multi scale gradient watershed hierarchies." *IEEE Transactions on Image Processing*, vol. 8, Issue: 1, Jan. 1999, pp. 69-79

[3] K. Haris, S. N. Efstratiadis, N. Maglaveras, and A. K Katsaggelos, "Hybrid image segmentation using watersheds and fast region merging." *IEEE Transactions on Image Processing*, vol. 7, Issue: 12, Dec. 1998, pp. 1684-1699.

[4] P. Jaesang and J. M. Keller, "Snakes on the watershed." *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 23, Issue: 10, Oct. 2001, pp. 1201-1205.

[5] S. Lingxiong, R. M. Lewitt, J. S. Karp, and G. Muehllehner, "Combination of Wiener filtering and singular value decomposition filtering for volume imaging PET" *IEEE Transactions on Nuclear Science*, vol. 42, Issue: 4, Aug. 1995, pp. 1228-1234.

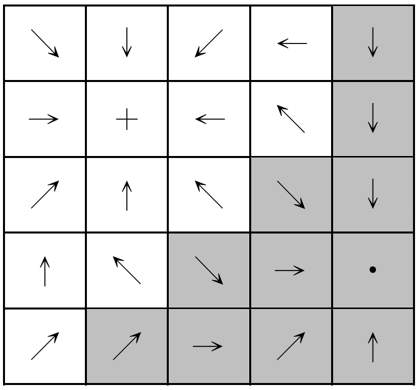
[6] L. Najman and M. Schmitt, "Geodesic saliency of watershed contours and hierarchical segmentation." *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 18, Issue: 12, 1996, pp. 1163-1173.

[7] F. J. Sanchez-Marin, Y. Srinivas, K. N. Jabri, and D. L. Wilson, "Quantitative image quality analysis of a nonlinear spatio-temporal filter." *IEEE Transactions on Image Processin*g, vol. 10, Issue: 2, Feb. 2001, pp. 288-295.

[8] L. Vincent and P. Soille, "Watersheds in digital spaces: an efficient algorithm based on immersion simulations." *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 13, Issue: 6, June 1991, pp. 583 -598.

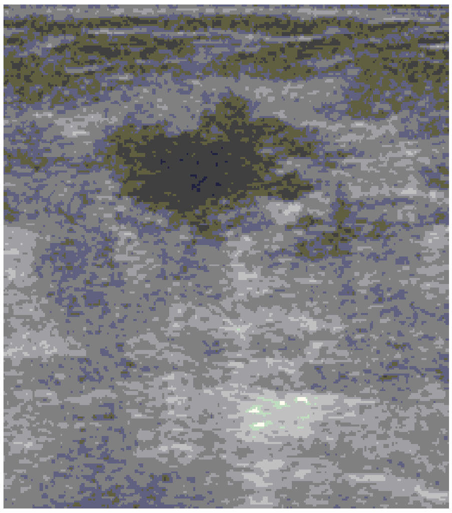
16.9	19.3	13.6	20.6	31.3
18.8	12.0	15.5	23.4	20.5
20.2	22.0	26.7	20.9	17.4
25.4	22.9	21.0	19.9	15.2
30.8	35.6	30.0	18.8	17.7

(a)

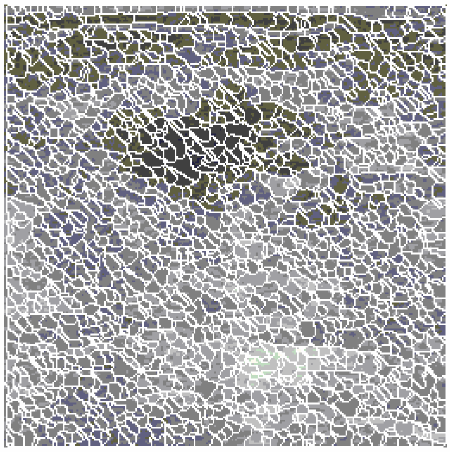


(b)

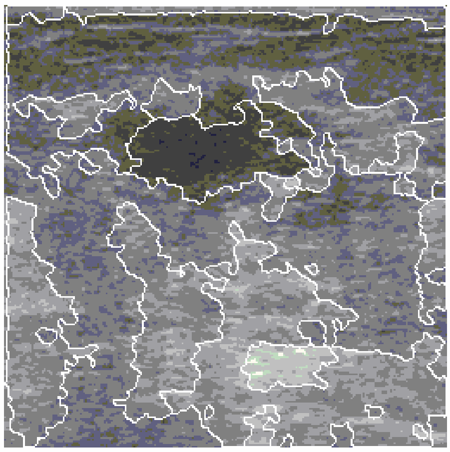
Fig. 1. (a) GMI values: The pixels 12.0 and 15.2 correspond to LIMs and (b) gradient vectors indicate the direction toward the lowest value 8-neighbor at each point. Two watersheds regions are obtained.



(a)



(b)



(c)

Fig. 2. (a) An original breast ultrasonic image, (b) the processed image after medium filtering and watershed transformation (1679 regions), and (c) merging based on region homogeneity (26 regions).

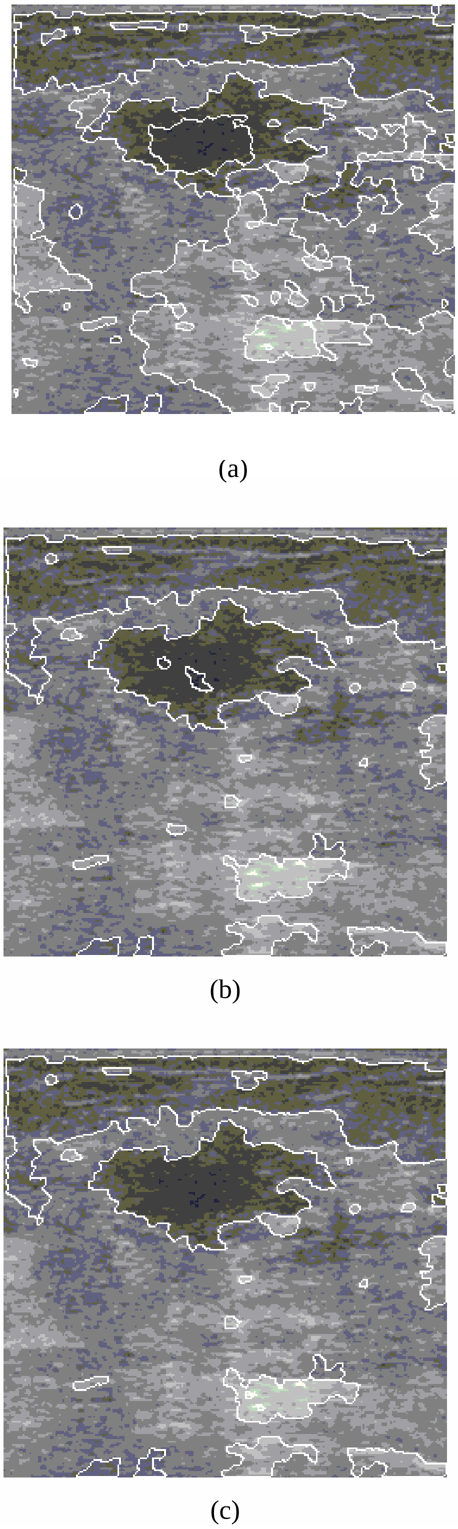


Fig. 3. Final segmentation: (a) using the single weight factors (69 regions), and (b) using the identical weight factors (25 regions), and (c) using the selected weight factors (26 regions).

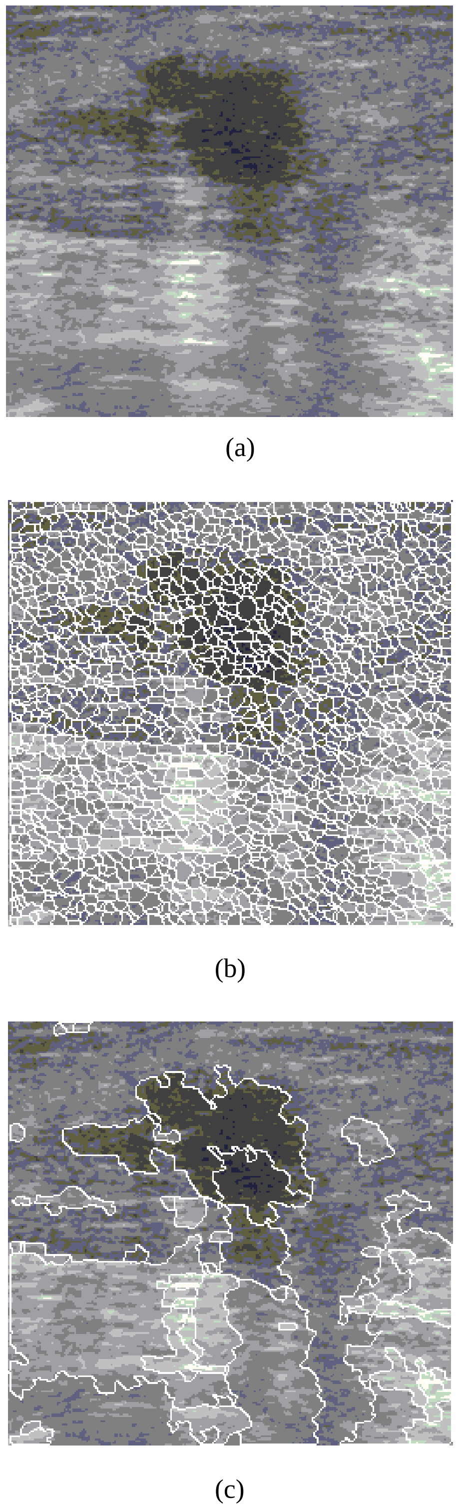
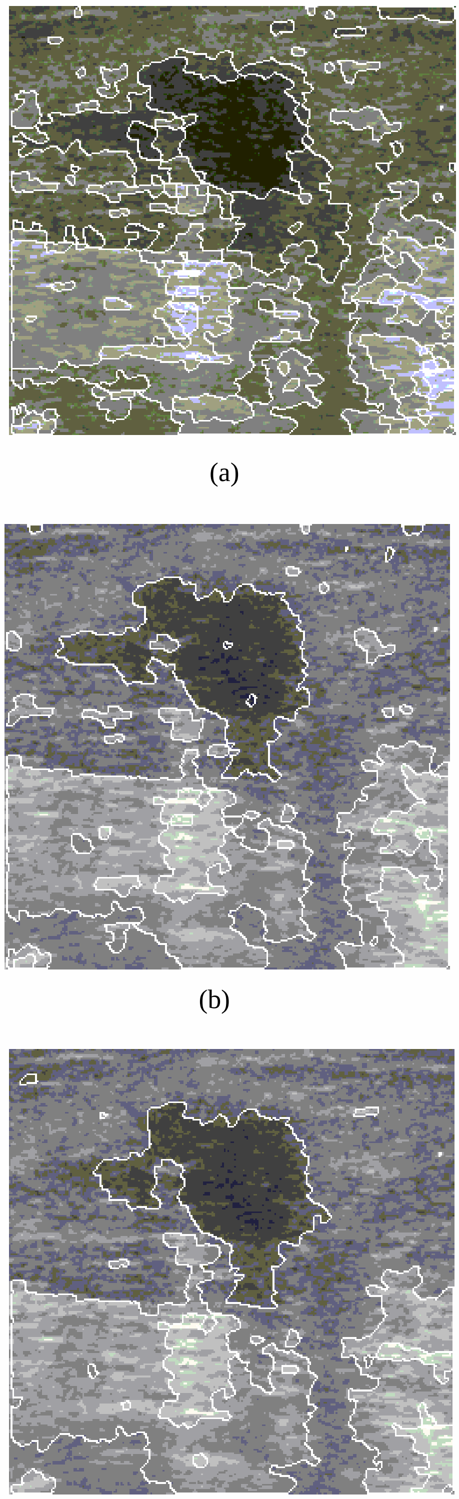
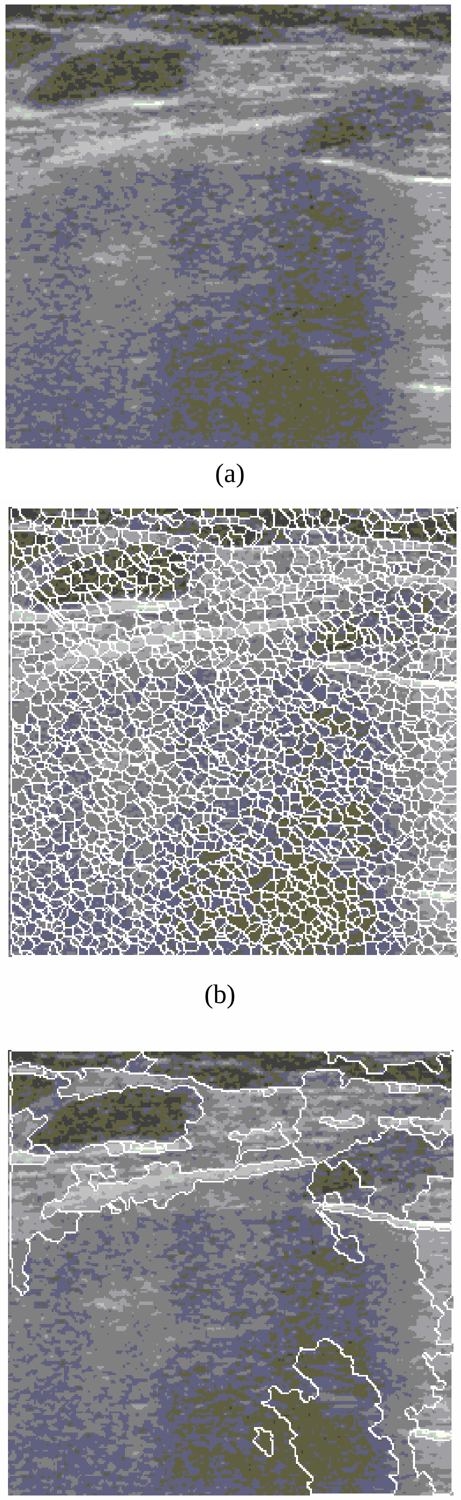


Fig. 4. (a) An original breast ultrasonic image, (b) the processed image after medium filtering and watershed transformation (1662 regions), and (c) merging based on region homogeneity (42 regions).



(a) (b) (c)

Fig. 5. Final segmentation: (a) using the single weight factors (78 regions), and (b) using the identical weight factors (39 regions), and (c) using the selected weight factors (22 regions).



(a) (b) (c)

Fig. 6. (a) An original breast ultrasonic image, (b) the processed image after medium filtering and watershed transformation (1672 regions), and (c) merging based on region homogeneity (36 regions).

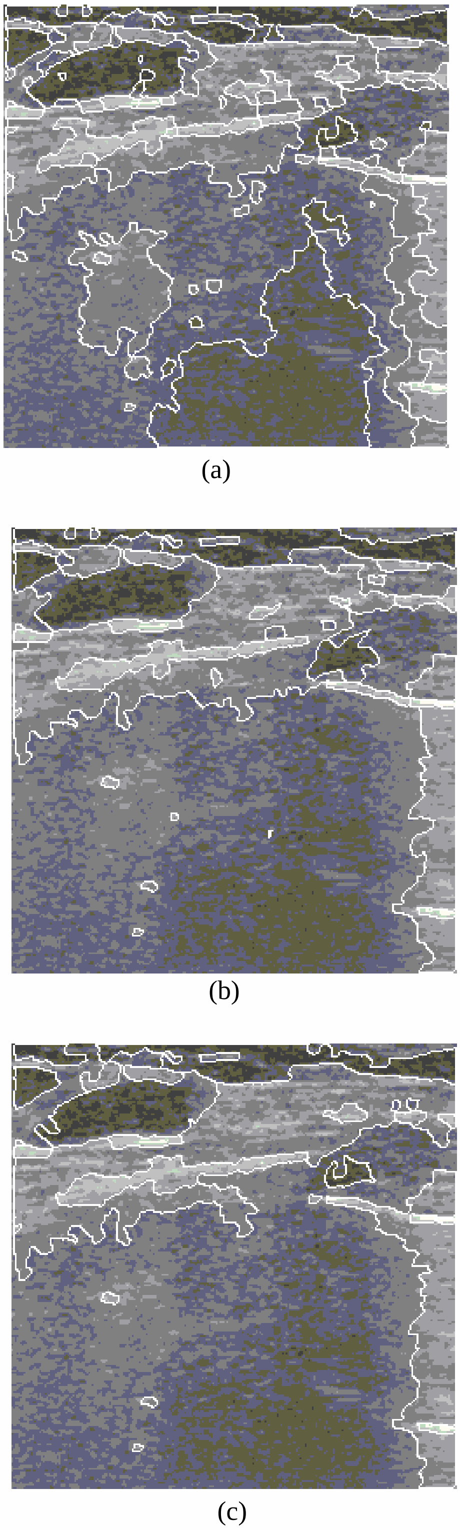


Fig. 7. Final segmentation: (a) using the single weight factors (77 regions), and (b) using the identical weight factors (33 regions), and (c) using the selected weight factors (27 regions).

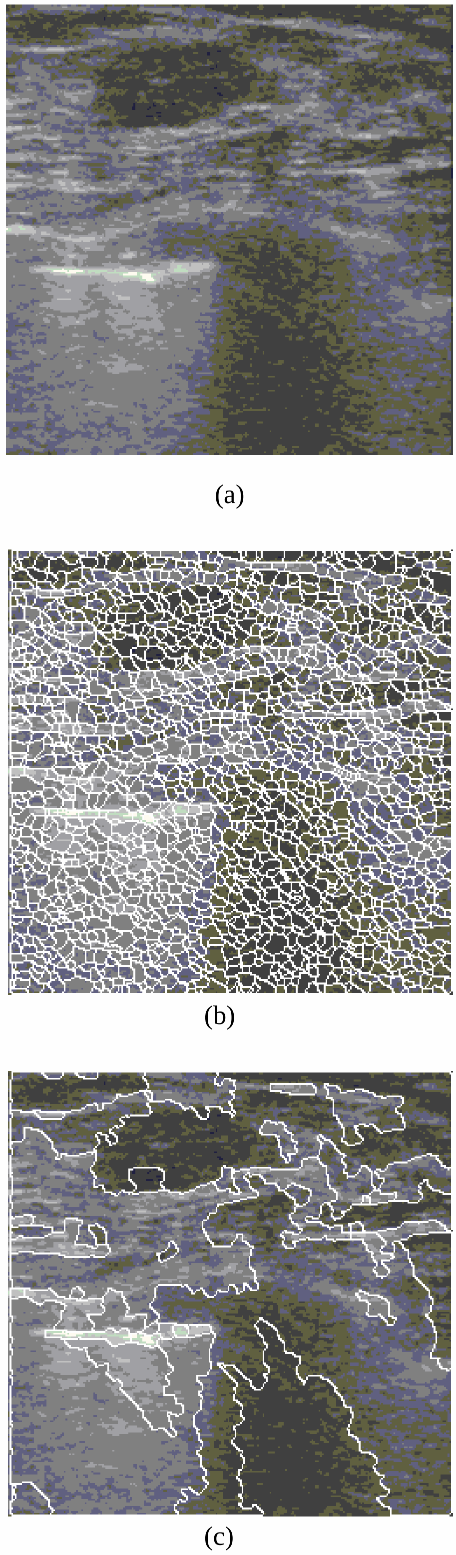
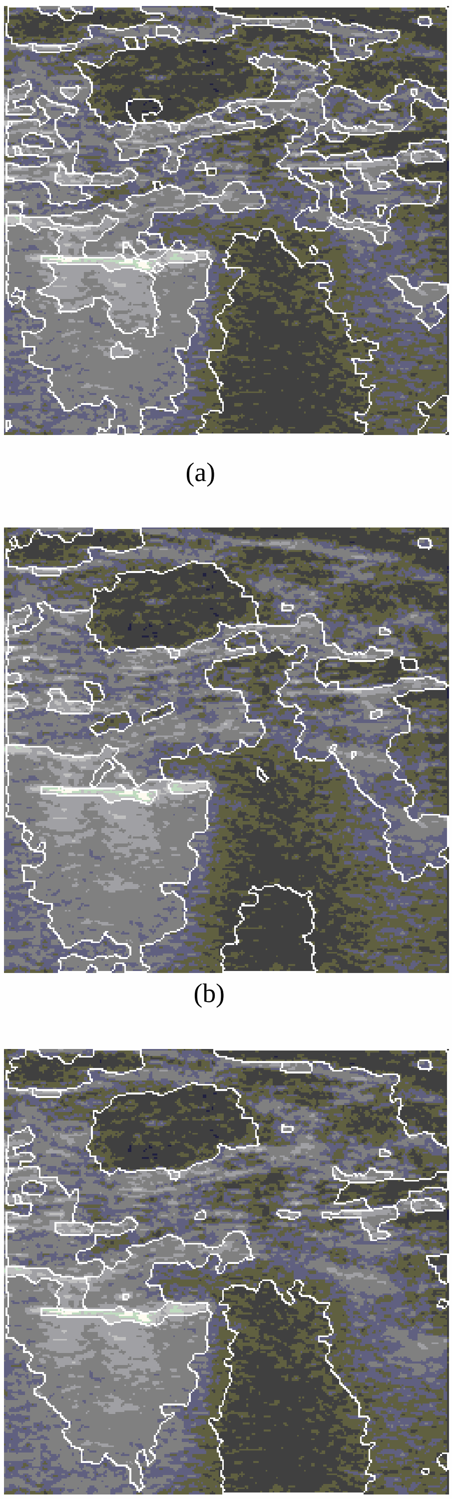


Fig. 8. (a) An original breast ultrasonic image, (b) the processed image after medium filtering and watershed transformation (1641 regions), and (c) merging based on region homogeneity (43 regions).

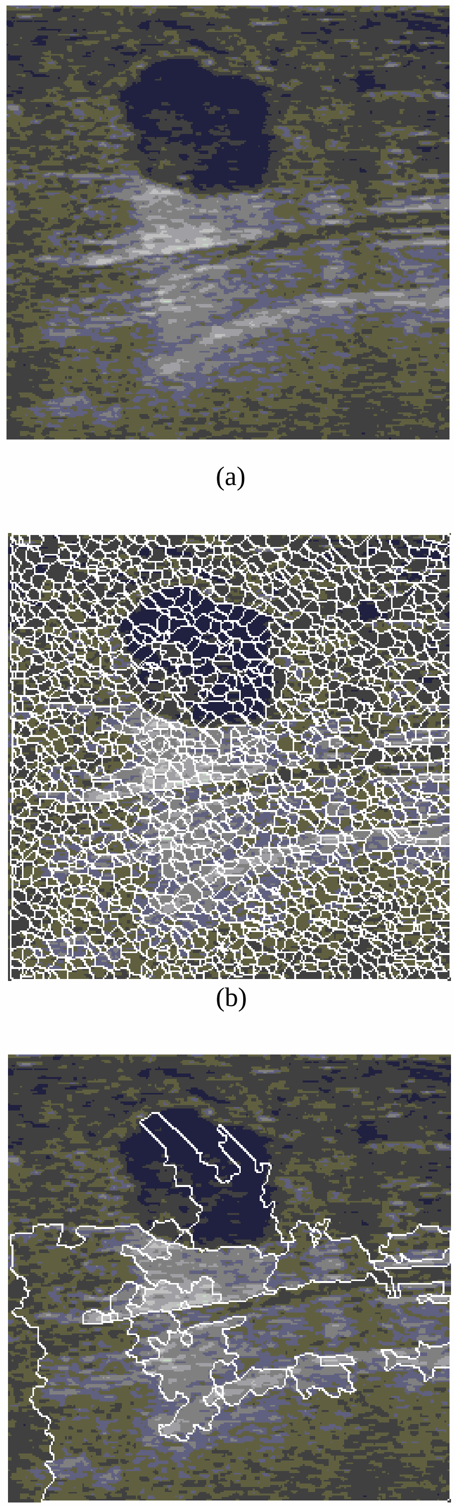


(a)

(b)

(c)

Fig. 9. Final segmentation: (a) using the single weight factors (68 regions), and (b) using the identical weight factors (32 regions), and (c) using the selected weight factors (30 regions).

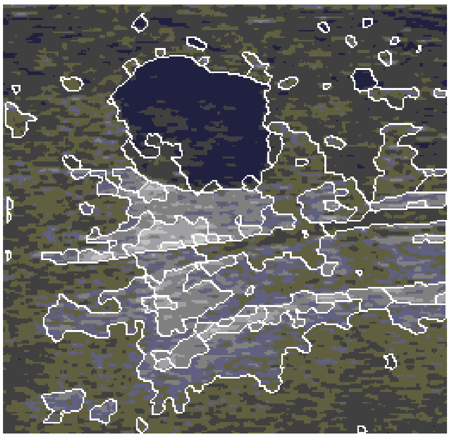


(a)

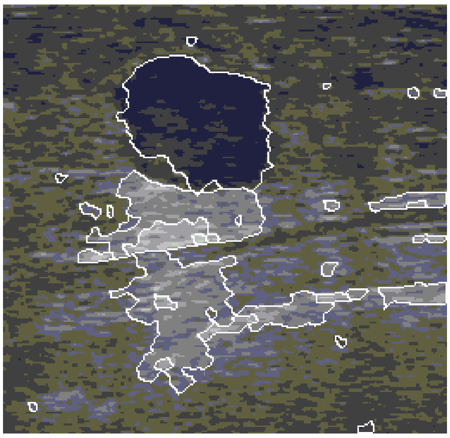
(b)

(c)

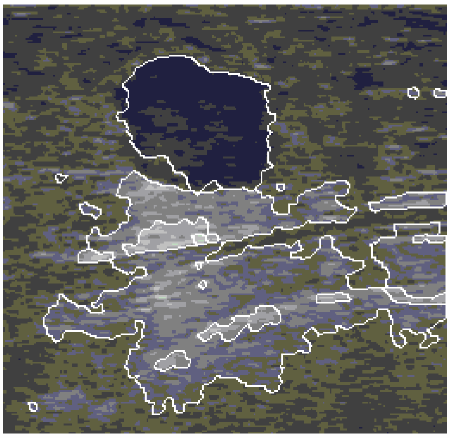
Fig.10. (a) An original breast ultrasonic image, (b) the processed image after medium filtering and watershed transformation (1496 regions), and (c) merging based on region homogeneity (32 regions).



(a)



(b)



(c)

Fig. 11. Final segmentation: (a) using the single weight factors (54 regions), and (b) using the identical weight factors (25 regions), and (c) using the selected weight factors (22 regions).