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● *Original Contribution*

WATERSHED SEGMENTATION FOR BREAST TUMOR IN 2-D SONOGRAPHY

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Abstract—Automatic contouring for breast tumors using medical ultrasound (US) imaging may assist physicians without relevant experience, in making correct diagnoses. This study integrates the advantages of neural network (NN) classification and morphological watershed segmentation to extract precise contours of breast tumors from US images. Textural analysis is employed to yield inputs to the NN to classify ultrasonic images. Autocovariance coefficients specify texture features to classify breasts imaged by US using a self-organizing map (SOM). After the texture features in sonography have been classified, an adaptive preprocessing procedure is selected by SOM output. Finally, watershed transformation automatically determines the contours of the tumor. In this study, the proposed method was trained and tested using images from 60 patients. The results of computer simulations reveal that the proposed method always identified similar contours and regions-of-interest (ROIs) to those obtained by manual contouring (by an experienced physician) of the breast tumor in ultrasonic images. As US imaging becomes more widespread, a functional automatic contouring method is essential and its clinical application is becoming urgent. Such a method provides robust and fast automatic contouring of US images. This study is not to emphasize that the automatic contouring technique is superior to the one undertaken manually. Both automatic and manual contours did not, after all, necessarily result in the same factual pathologic border. In computer-aided diagnosis (CAD) applications, automatic segmentation can save much of the time required to sketch a precise contour, with very high stability. (E-mail: ylhuang@mail.thu.edu.tw)

Key Words: **Breast sonography, Textural analysis, Neural network, Watershed transform, Tumor contour approximation.**

INTRODUCTION

Both medical mammographic images and sonographic images can be used to detect and diagnose breast tumors. (Shankar et al. 1993; Petrick et al. 1996; Dhawan et al. 1996). Although mammography can visualize nonpalpable and minimal tumors, ultrasound (US) is certainly a convenient and safe tool for diagnosing breast tumors, particularly palpable tumors. Modern medical US equipment performs real-time high-resolution imaging without the use of ionizing radiation, and it is relatively inexpensive and portable. The cost-effectiveness and portability of this facility are particularly important in smaller hospitals, in which the equipment is useful in conducting complex medical imaging in a timely manner. Ultrasonic images are markers for the early detection of some breast cancers. The use of ultrasonic images to analyze the homogeneity of an internal echo can assist in differentiating between benign and malignant lesions. Garra et al. (1993) asserted that sonographic textural analysis is a simple method for substantially reducing the number of benign lesion biopsies. Moreover, Chen et al. (1999, 2000a, 2000b, 2002) presented various computer-aided diagnosis (CAD) systems to distinguish benign from malignant tumors by applying neural networks. The proposed CAD systems diagnose breast tumors by exploiting interpixel correlations within the manually extracted ultrasonic subimage of the region-of-interest (ROI). Such CAD systems perform differential diagnosis based on a manually sketched ROI very effectively. Experienced radiologists can identify a tumor in an ultrasound image from a tumor shape and the contrast of internal echoes. However, a digital ultrasonic image always includes speckle, noise and tissue-related textures, as depicted in Fig. 1. Information about shape, provided by a tumor contour, is important

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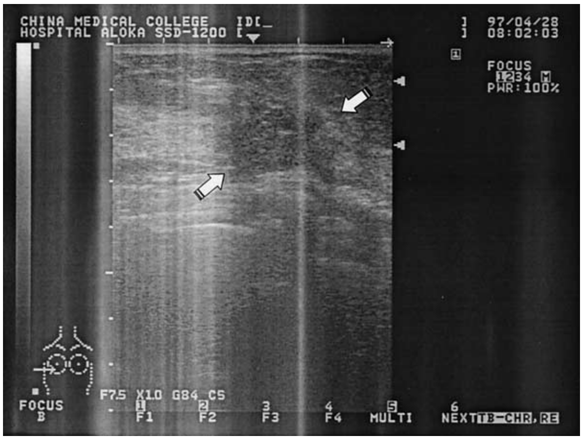

Fig. 1. A 736 × 556 digital image is captured from the sonographic scanner. Note that there are 58 × 58 = 3364 pixels in a 1 cm × 1 cm rectangle.

to physicians in making diagnostic decisions. A previously proposed CAD algorithm has been shown effectively and reliably to distinguish between benign and malignant lesions by considering the tumor shape. The appearance of the proposed shape features was almost independent of the sonographic gain setting and could tolerate reasonable variation in boundary delineation associated with the different machines used. In practice, contouring tumors in a digitized ultrasonic image is difficult and time-consuming. As US imaging becomes increasingly widespread, the clinical application of an effective automatic contouring method is becoming urgent. A precise US image segmentation method can facilitate an accurate diagnosis of a breast tumor.

Most conventional edge-based segmentation methods depend on the gradient of an image to determine the boundary of an object. Such methods are not designed to detect discontinuities of image intensity, so edge-based methods do not perform well when applied to an ultrasonic image. Region-based segmentation methods, such as split-and-merge, region-growing, snake-deformation and morphological watershed transformation, are sensitive to noise and contrast in an image (Boukerroui et al. 1998; Ladak et al. 2000; Horsch et al. 2001; Hsu et al. 2001; Overhoff et al. 2002). The speckle, weak edges and tissue-related textures in US image prevent most split-and-merge and region-growing models from being able to determine the desired boundary of the tumor satisfactorily. The snake-deformation model is an extensively used means of determining the boundary of an object-of-interest in US image (Chen and Lu 2000; Chen et al. 2000, 2003). Determining the real boundary of a region by applying the snake-deformation process depends on an initial estimate of contours. However, automatically generating a fitted initial contour is very difficult; furthermore, the snake-deformation procedure is very time-consuming. The watershed transformation, which is a reliable unsupervised model, was applied to solve diverse image-segmentation problems. Preprocessing procedures have been presented to improve the effectiveness of watersheds in various approaches (Detmer et al. 1990; Han et al. 1991; Choy and Jin 1996; Richard and Czerwinski 1999). However, the varieties of tissues in a breast US image are many and boundary discontinuities often cause difficulties in extracting accurate contours of a tumor. Hence, this study describes an adaptive texture-based preprocessing filter as part of the proposed contour-detection method, to reduce the noise, the amount of speckle and the presence of tissue-related texture in ultrasonic images of breasts. The proposed approach integrates the advantages of NN classification and watershed-segmentation methods to extract contours of a breast tumor from US images.

MATERIALS AND METHODS

Imaging data acquisition

An ultrasonic image database included 60 US images of pathologically proven benign breast tumors from 21 patients and carcinomas from 39 patients (the largest diameter of tumor > 1 cm in all cases). The database included only one image from each patient. The US images were captured at the largest diameter of each tumor. The 60 images considered herein were randomly selected from almost 250 images collected between January 1, 1997 and May 31, 1999. The patients' ages ranged from 18 to 62 years. Ultrasound imaging was performed using an Aloka SSD 1200 (Tokyo, Japan) scanner and a 7.5-MHz linear array transducer with freeze-frame capability. No acoustic stand-off pad was used. The entire database was supplied by the coauthor, an experienced physician, D-R. Chen from the Department of General Surgery, China Medical College and Hospital, Taichung, Taiwan. When a sonogram was performed, an analog video signal was transmitted from the VCR output of the scanner to the image-acquiring computer; the data were then digitized using a frame-grabber, Video CATcher (Top Solution Technology Co, Taipei, Taiwan). The capturing resolution of the external frame grabber was 736 × 566 pixels for an NTSC video screen picture. ProImage® (Prolab, Taipei, Taiwan) software package was used to perform digital sonography in real-time. Each monochrome ultrasonic image was quantized into 8 bits with 256 grey levels. D-R. Chen manually determined the contours of the tumor and then saved them in files for comparison with the automatically generated contours.

Textural analysis

An ultrasonic image is comprised of several points with different grey-level intensities. Different tissues have considerably different textures. The correlation between the grey levels of neighboring pixels within images was exploited as textural features to discriminate the breast ultrasonic images. The 2-D normalized autocorrelation coefficients (Gonzalez and Woods 2002) were used to specify the interpixel correlation within an image. Furthermore, these coefficients were further modified into a mean-removed version to generate the autocovariance coefficients for images with a different brightness, but with a similar texture. The 2-D autocovariance coefficient between pixel (i, j) and pixel $(i + \Delta m, j + \Delta n)$ in an image of size $M \times N$ is given by:

$$\gamma(\Delta m, \Delta n) = \frac{A'(\Delta m, \Delta n)}{A'(0, 0)}, \tag{1}$$

where

$$A'(\Delta m, \Delta n) = \frac{1}{(M - \Delta m)(N - \Delta n)} \sum_{x=0}^{M-1-\Delta m} \sum_{y=0}^{N-1-\Delta n} |(f(x, y) - \bar{f})(f(x + \Delta m, y + \Delta n) - \bar{f})| \tag{2}$$

where $\bar{f}$ is the average value of $f(x, y)$. Previous studies have determined that the 2-D autocovariance coefficients can be used to specify the interpixel features and, thus, to distinguish the differences among breast tumors (Chen et al. 1999, 2000a).

Neural network classification and image preprocessing

A self-organizing map (SOM) neural network (Kohonen 1988) includes an input layer, a single hidden layer and a mapping array of outputs, as shown in Fig. 2. It refers to the ability to perform unsupervised learning. The number of input neurons is determined by the number of dimensions of the input vectors. In general, the SOM model defines a mapping from the higher-dimensional input data space to a regular 2-D mapping array. A parametric weight vector generated by a learning algorithm is associated with every neuron in the mapping array. An input vector is compared with all weight vectors and the best matching input vector is defined as the corresponding SOM response. Each neuron in the mapping array may also be given a class label, using training samples to increase the usefulness of the analysis. During the weight-modification phase of the learning algorithm, the learning rate parameter and the radial coordinate of the point at which the weight is modified monotonically decline over time. The SOM models exhibit high unsupervised learning capability and computational efficiency. The proposed contour-detection system classifies breast ultrasonic images by adding the final SOM mapping array.

The modified 2-D normalized autocovariance coefficients and the variance of the image are used as the inputs in the SOM model. The number of dimensions of the matrix can be fixed for any size of image. The autocovariance matrix is initially determined from the textural features in an ultrasonic image. The coefficients and the variance of the image are formed as the feature vector. Thereafter, the SOM model is used to determine the textural class of the breast US image. A specially designed preprocessing filter is applied to the ultrasonic image for each textural class in the SOM model. The preprocessing procedure can reduce the amount of speckle, the amount of noise and the number of tissue-related textures in ultrasonic images and preserve the shape and contrast of a tumor.

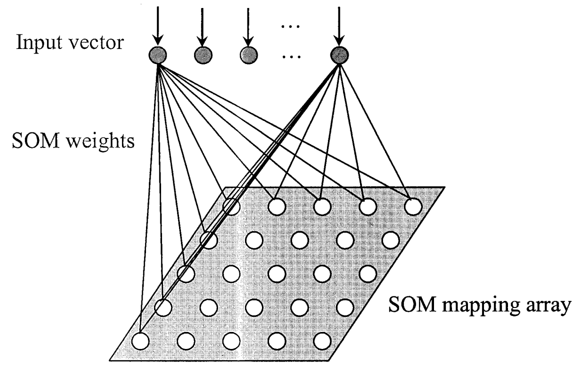

Fig. 2. Structural graph of the SOM neural network.

Watershed transformation

One of the most reliable methods of automatic and unsupervised segmentation is the watershed transformation (Vincent and Soille 1991; Najman and Schmitt 1996). This technique has been applied successfully to solve a wide range of difficult problems of image segmentation. Breast ultrasonic images are herein identically considered to be a 3-D topographic surface. The intensity of a pixel in the image represents the elevation of the corresponding position. The purpose of the watershed transformation is to determine the watershed lines on a topographic surface. Figure 3 shows the watershed transformation to be applied to a topographic surface of an ultrasonic image. Suppose that each regional minimum of the surface has holes. The topography is then flooded from the bottom and the flooding liquid rises through the holes. Dams are built to prevent the merging of the liquid that rises through two adjacent minima. Eventually, each regional minimum is surrounded by dams. These dams correspond to the lines that separate the watersheds. The watershed algorithm accordingly determines the continuous boundaries in an image.

However, the watershed transformation may oversegment ultrasonic images. Oversegmentation generates incorrect contours of breast tumors because sonographic images

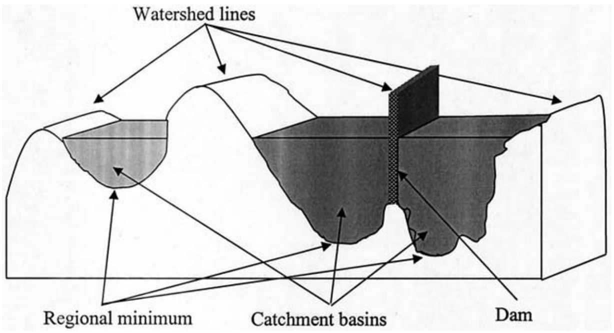

Fig. 3. Topographic view of watershed transformation.

include noise, speckle and irregular textures. As presented in Fig. 4b, oversegmentation can be sufficiently serious to render incorrect segmentation results. Several approaches have been developed to solve this problem (Beucher and Meyer 1993; Haris and Efstratiadis 1998; Bleau and Leon 2000; Lotufo and Falcao 2000). One sophisticated method for controlling oversegmentation is based on markers. A marker was defined as a connected component in an image. In a connected component, the grey levels of pixels must satisfy specified criteria of similarity. The marker is usually selected from the preprocessed image by applying the set of criteria. Lotufo and Falcao (2000) proposed an algorithm for detecting watershed boundaries based on similarity using the markers. The similarity-based watershed algorithm is performed herein to control oversegmentation in ultrasonic images. A marker is defined as a region that is surrounded by pixels of higher altitude (larger grey level). In this study, markers are selected by applying simple procedures that are based on grey level and connectivity.

Determining contours of breast tumors

In the presented contouring method, the modified autocovariance coefficients are initially computed from the US image. The coefficients and the variance of the image are expressed as a 25-dimensional feature vector. The SOM model employed the feature vector to determine the textural in each breast ultrasonic image. The SOM learning algorithm is an unsupervised, iterative vector quantization that converts complex, nonlinear statistical data items from a high-dimensional space onto simple reference vectors in a low-dimensional space. The algorithm is considered overall to perform a function similar to mapping in the brain of a higher biological organism. The implementation of the learning algorithm is reiteratively executed from the training vectors to produce the synaptic weight vectors applied by the SOM model.

The preprocessing filtering procedures are especially designed to be applied to ultrasonic images of breast tumors. Various preprocessing filters that satisfac-

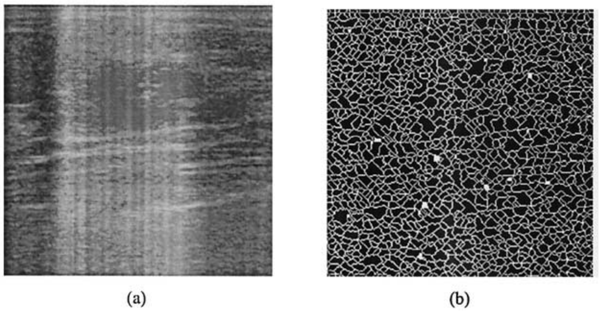

Fig. 4. Illustration of oversegmentation: (a) A breast US image, and (b) result of applying the watershed algorithm in Vincent and Soille (1991).

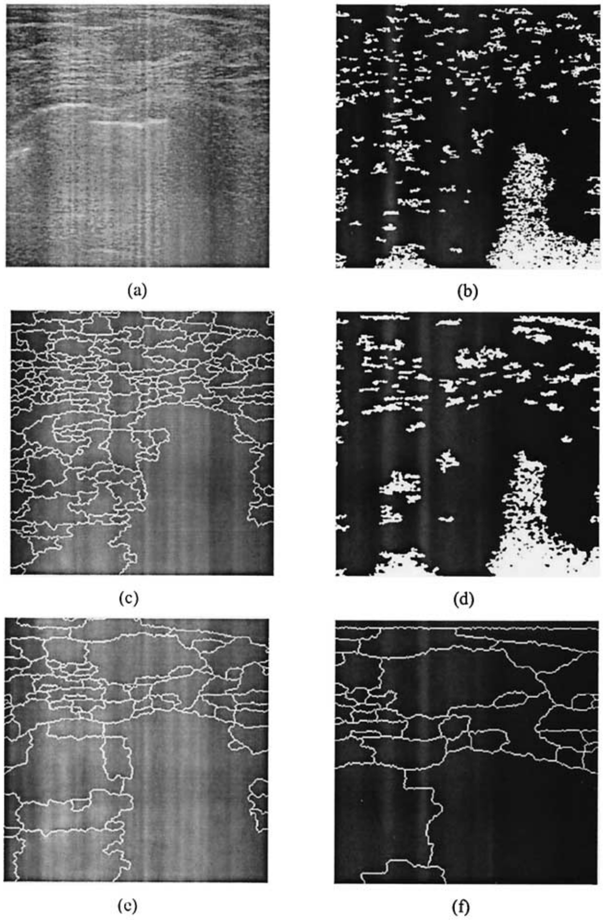

Fig. 5. Watershed segmentation with the distinct preprocessing: (a) The original image; (b) the markers generated without preprocessing; (c) watersheds generated without preprocessing; (d) the marker generated by the image through with 3 × 3 Wiener filtering; (e) watersheds generated by the preprocessed image (5 × 5 Wiener filtering) and the marker (d); and (f) watersheds generated by the preprocessed image (3 × 3 Wiener filtering) and the marker (d).

torily reduce the amount of speckle, the noise and the number of tissue-related textures in breast US images were considered. An effective filter was developed to eliminate useless information from the US images, associated with each textural class. After the original US image was preprocessed by filtering, the similarity-based watershed algorithm was applied to identify the contours of the breast tumors.

Watershed segmentation always yields poor contours of the breast tumor when the selected marker is not sufficiently efficient. In this study, a 2-D minimum mean-square error filter, the Wiener method, is applied as the primary preprocessing method to suppress the problematic noise and, thus, to generate more precise markers. The Wiener method is a pixel-wise adaptive low-pass filtering method based on statistics estimated from the local neighborhood of each pixel. Wiener filters were determined herein to be useful for smoothing ultrasonic images. For example, Fig. 5a presents an original breast US image of a benign tumor. Figure 5b presents the image of the markers generated without preprocessing filtering. Similarity-based watershed detection of the markers is performed. As indicated in Fig. 5c, the determined boundaries still cause oversegmentation. Figure 5d shows the markers generated using the 3 × 3 Wiener filter. The markers in Fig. 5d can clearly be seen to be more efficient than those in Fig. 5b. In practice, the watershed algorithm always yields better segmentation results when more accurate markers are used. Figure 5e and f presents the watersheds of the ultrasonic image obtained using 5 × 5 and 3 × 3 Wiener filters, respectively. Both results of the segmentation of the breast tumor are better than presented in Fig. 5c. Furthermore, the contour in Fig. 5e is quite similar to the manually sketched contours of the breast tumor in Fig. 5f. The results indicate that texture-based SOM preprocessing is a very effective procedure for increasing the accuracy of contours of a breast tumor in US image. Figure 6 presents a flowchart of the proposed method, in a form that includes the preprocessing and segmentation phases.

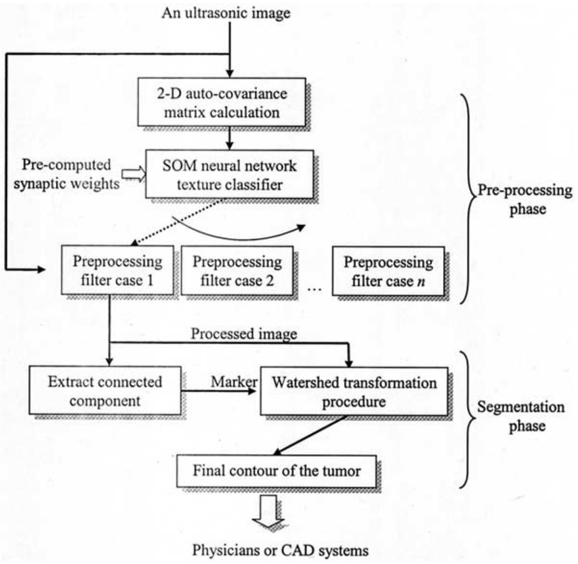

Fig. 6. The flowchart of the proposed method.

Table 1. The pathology-proven result, size of ROI, SOM class, precision ratio (PR) and match rate (MR) for the breast US images outside the training set

Test image no.	Pathology-proven result	ROI size (cm) width × height	SOM class	PR (%)	MR (%)
1	Malignant	1.89 × 1.06	1	86.00	99.44
2	Malignant	2.56 × 1.25	3	84.77	98.98
3	Malignant	1.61 × 1.04	7	85.20	96.97
4	Malignant	1.18 × 0.90	4	82.24	97.17
5	Malignant	0.64 × 1.46	8	74.33	98.25
6	Malignant	1.46 × 0.58	6	87.23	93.89
7	Malignant	1.46 × 1.28	8	78.25	95.49
8	Malignant	1.66 × 1.35	9	74.90	84.14
9	Malignant	2.33 × 2.54	6	80.69	85.64
10	Malignant	2.06 × 1.02	1	87.72	93.66
11	Malignant	1.94 × 1.06	1	86.26	91.39
12	Malignant	1.01 × 0.92	3	86.13	95.81
13	Malignant	1.54 × 1.27	4	81.91	97.54
14	Benign	1.56 × 0.94	3	67.56	93.30
15	Benign	1.35 × 0.63	2	71.70	83.11
16	Benign	0.90 × 0.42	6	80.71	99.43
17	Benign	1.32 × 0.56	6	82.81	95.84
18	Benign	1.52 × 0.78	2	84.34	97.37
19	Benign	1.52 × 0.59	5	82.43	97.05
20	Benign	1.90 × 0.83	1	88.80	98.74
Average				81.70	94.66

RESULTS

This section develops a method for evaluating contours to analyze the effectiveness of the proposed method. In the simulations, a SOM neural network was used as a nonlinear and unsupervised classifier of textures. The SOM with the size of mapping array was 3×3 neurons. The SOM output is used to determine the textural class for US image. A total of 40 US images were used to train the SOM model and the other 20 images were used to evaluate the performance of the proposed method for determining contours. The training set and test set were randomly selected from a database of ultrasonic images. In the preprocessing phase, the Wiener filters importantly reduced speckle, noise and tissue-related textures from the US images. The precision ratio (PR) and the match rate (MR) between the manually determined contours and the automatically detected contours were calculated to evaluate the performance numerically. The PR is defined as:

$$\mathrm{PR} = \left(\frac{N_{\mathrm{diff}}}{N_M}\right) \times 100\%, \tag{3}$$

where N_{diff} is the number of pixels that differ between the manually determined contour and the automatically determined contour and N_M is the number of pixels in the manual contour. The MR is defined as:

$$\mathrm{MR} = \left(1 - \frac{|\mathrm{Area}_M - \mathrm{Area}_W|}{\mathrm{Area}_M}\right) \times 100\%, \tag{4}$$

where Area_M and Area_W denote the superficial measurements covered by the manually sketched contours and those covered by the contours generated by the proposed system, respectively.

Table 1 lists the pathology-proven results, including ROI size of breast tumor, SOM textural class, PR and MR, for the 20 US images outside the training set. Figures 7a, 8a and 9a, show the original magnified monochrome breast US images no. 7 (malignant case), no. 13 (malignant case) and no. 19 (benign case), respectively. Figures 7b, 8b and 9b show the contours manually sketched with reference to the corresponding US images. Figures 7c, 8c and 9c plot the contours determined by the proposed system. The proposed system clearly yields contours that are similar to those manually sketched.

DISCUSSION

This article presented an efficient method for automatically detecting contours of breast tumors in sonography. From our experiences, the computing time of the snake-deformation model is 100 times longer than that of the proposed method. The proposed method integrates the advantages of unsupervised neural networks with those of authentic watershed segmentation. The texture-based pre-

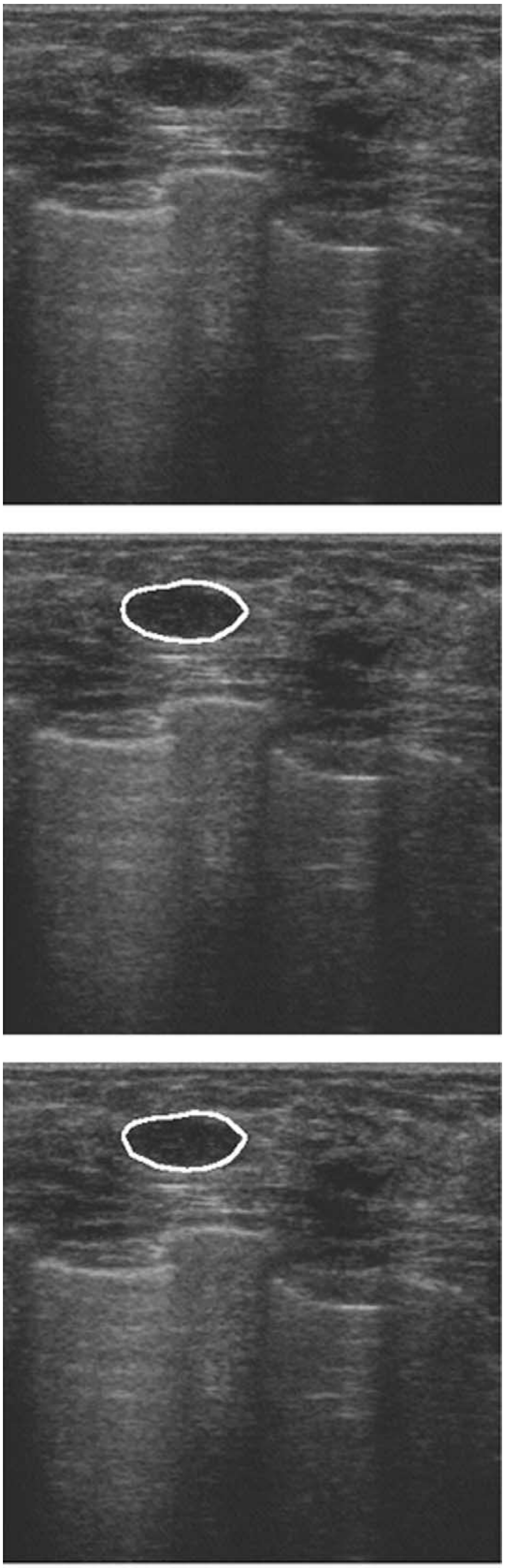

Fig. 7. Results of contour segmentation: (a) Original magnified monochrome breast US images no. 7 (malignant case); (b) manual sketch contour; and (c) automatic sketch contour.

Fig. 8. Results of contour segmentation: (a) Original magnified monochrome breast US images no. 13 (malignant case); (b) manual sketch contour; and (c) automatic sketch contour.

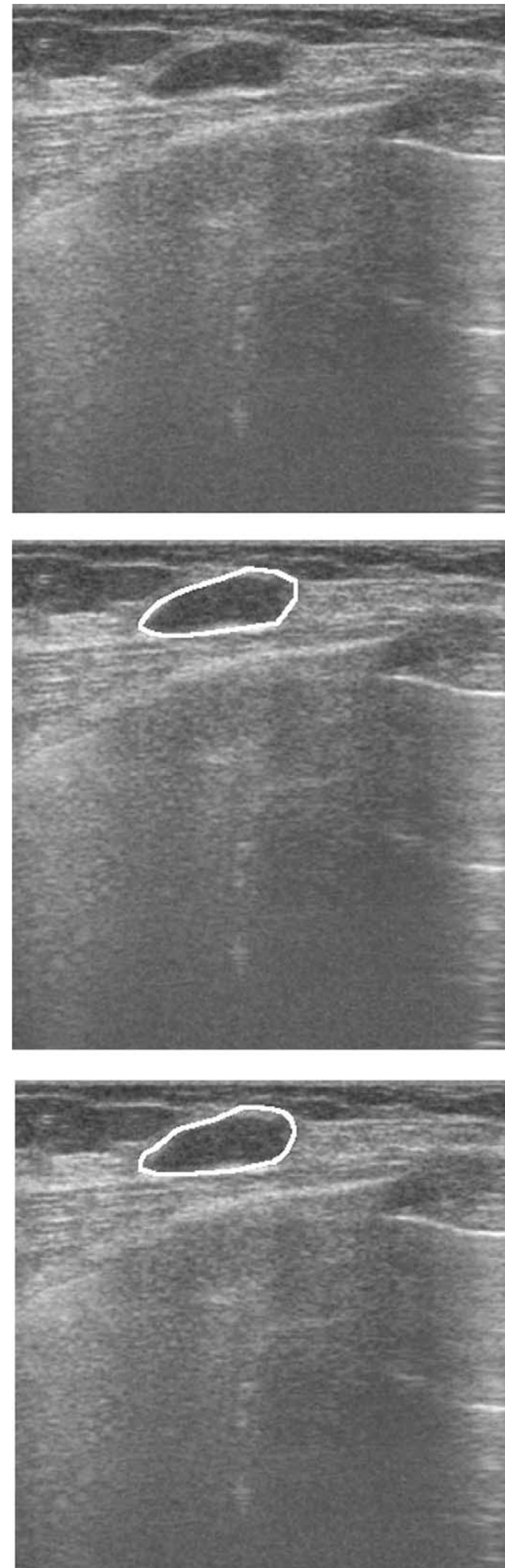

Fig. 9. Results of contour segmentation: (a) Original magnified monochrome breast US images no. 19 (benign case); (b) manual sketch contour; and (c) automatic sketch contour.

processing of the proposed method applies a SOM model to classify input images. An unsupervised learning algorithm is used to generate the synaptic weights for use by the SOM classifier. Moreover, preprocessing filters are especially designed for each textural class and, then, the similarity-based watershed algorithm automatically produces the contour of the tumor. The preprocessing phase prevents oversegmentation and improves the watershed segmentation. The 60 cases used in this study were randomly selected from nearly 250 images. The proposed method determines the contours of breast tumors in US images that are very similar to manually sketched contours. The experimental results reveal that the proposed method can practically determine the contours of a breast tumor from US images. Also, superficial measure and shape information from automated contours can be used in clinical diagnosis. This study is not to emphasize that the automatic contouring technique is superior to the one undertaken manually. Both automatic and manual contours did not, after all, necessarily result in the same factual pathologic border. However, in CAD applications, automatic segmentation can save much of the time required to sketch a precise contour with very high stability. Physicians always make dissimilar manual contours of a tumor in different times. Future work should employ the proposed method to derive the precise shapes of tumors in 3-D US images. Information about the shape and volume of a tumor in US image may be important to physicians in making diagnoses. A physician cannot manually sketch the contours of a tumor in a 3-D sonography of many hundreds of 2-D images. The development of this automatic contouring method is indeed important and its medical application is urgent.

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