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A Disk Expansion Segmentation Method for Ultrasonic Breast Lesions

Chih-Kuang Yeh, Yung-Sheng Chen, Wei-Che Fan, Yin-Yin Liao
Department of Biomedical Engineering and Environmental Sciences,
National Tsing Hua University, Hsinchu, Taiwan, ROC

Department of Electrical Engineering, Yuan Ze University, Chungli, Taiwan, ROC

Corresponding author for reprint requests:
Name: Chih-Kuang Yeh, Ph.D.
Address: Department of Biomedical Engineering and Environmental Sciences
National Tsing Hua University
101, Section 2, Kuang-Fu Road,
Hsinchu, Taiwan 30013, ROC
Phone: +886-3-5715131 ext 34240
Fax: +886-3-5718649
E-mail: ckyeh@mx.nthu.edu.tw
Abstract

Automatically extracting lesion boundaries in ultrasound images is difficult due to the variance in shape and interference from speckle noise. An effective scheme of removing speckle noise can facilitate the segmentation of ultrasonic breast lesions, which can be performed with an iterative disk expansion method. In this study, a disk expansion segmentation method is proposed to semi-automatically find lesion contours in ultrasonic breast image. To evaluate the performance of the proposed method, the simulations with seven types of cysts, three in-vitro phantom images and ten clinical breast images are introduced. The mean normalized true positive area overlap between simulated contours and contours obtained by the proposed method is over 85% in simulation results. A strong correlation exists between physicians’ manual delineations and detected contours in clinical breast images. In addition, the method is also verified to be able to simultaneously contour multiple lesions in a single image. In comparison with the conventional active contour model, our proposed method does not require any initial seed within a lesion and thus, it is more convenient and applicable.

Key words: speckle noise, lesion contour, disk expansion method, computer-aided diagnosis (CAD).
1. INTRODUCTION

Medical ultrasound image has become a popular tool for early diagnosis of breast tumor. Unfortunately, the speckle brightness variations inherent in ultrasonic imaging degrade the image quality; and thus limit the detection of low contrast lesions and human interpretation. Therefore, many studies focused on development of speckle noise reduction technique to improve the image contrast resolution and the lesion texture extraction ability [1]-[6].

The lesion contour extraction provides significant clinical information to discriminate between benign and malignant tumors. Previous studies primarily focused on the lesion classification with manual delineations of the tumor boundaries [7]-[9]. However, the malignant tumor often embeds the surrounding tissue. As a result, the boundary with fine linear strands extending irregularly outward from the main tumor becomes obscure. Consequently, the work of manual delineation lesion by physicians is highly subjective judgment. In order to increase reliability of ultrasound lesion delineation and reduce the unnecessary operations such as biopsy and fine needle aspiration, the topic of computer-aided diagnosis for breast lesion detection has gained wide interest [10]-[14]. Computer-aided diagnosis (CAD) refers to the use of computerized analysis in helping physician to recognize abnormal areas in a medical
image. One goal of CAD is to increase the efficiency and effectiveness of breast
cancer screening by means of the computer as a second reader, and the other goal is to
classify the lesion as benign or malignant [13].

The active contour models (also called snakes) [15], the most popular CAD
technique, have been widely applied to segment the boundaries in ultrasound images
for the cortex of the brain [11], ovarian follicles [12], and left-ventricular boundaries
[16]. These models required an initial seed point and utilized a closed contour to
approach object boundary by iteratively minimizing an energy function. Since
inherent speckle interference obscures the ultrasound breast image, the active contour
models have poor convergence to lesion boundary concavity; and thus they can not
accurately contour the irregular shape malignant tumor. A modified model based on
involving an external force, called gradient vector flow (GVF) snake was proposed to
try to resolve the above mentioned problem [17]. The external force is a main
contribution to make GVF functioning. It means that the result will depend whether
the image quality can support an effective external force or not. Moreover, recent
general active contour approaches were proposed to achieve higher segmentation
accuracy and faster convergence [18]-[19].

In our previous study, we considered the image having degraded paint
characters (DPC) on the surface of road to demonstrate the closure noise property and showed a disk expansion method for the removal of closure noise [20]-[21]. From the viewpoint of image processing, when a thresholding process is applied on a gray-scale ultrasound image embedding speckle noises, the obtained binary image would be similar to a DPC image with closure noise. In order to detect ultrasonic breast lesions, the process of removing speckle noise may be included. Hence, the disk expansion (DE) scheme is mainly involved in our algorithm design to perform the boundary detection of an ultrasonic breast lesion.

To test the performance of the proposed algorithm, the simulations with seven types of cysts, three in-vitro phantom images and ten clinical breast images were adopted for experimentation. The extracted contours of clinical breast images were finally compared to those from ten experienced physicians’ manual delineations. Furthermore, the proposed algorithm also demonstrated the ability of simultaneously contouring multiple lesions in a single ultrasound image.

The paper is organized as follows. Section 2 presents the proposed algorithm, which includes adaptive thresholding, extracting significant object using disk expansion scheme, refining the extracted object, and extracting multiple objects.
Section 3 shows the results and gives a discussion, where simulation images with varying shape of cysts are introduced to test the proposed algorithm. The boundary error and area error estimates between the simulated contours and the contours obtained by the proposed algorithm are described, and the results of in-vitro phantom and clinical breast images are summarized for discussion. A conclusion is finally given in Section 4.

2. PROPOSED APPROACH

Figure 1 illustrates the flowchart of the proposed approach. Three primary parts of the proposed approach include: thresholding for converting a gray-scale ultrasound image into a binary image, disk expansion for extracting the significant object, and refining the extracted object for obtaining the more accurate object’s contour. In the flowchart, path (1) performs the primary object extraction task, whereas path (2) is used for rechecking and extracting the final result. The left path provides the original binary image and used for removing the extracted objects. Along the feedback path at right, the multiple significant objects can be extracted consequently. Note that the proposed approach is limited in contouring hypoechoic regions.

2.1. Adaptive Thresholding

According to the investigation on speckle image presented by Chen and Chen
[22], the uneven-brightness problem is one of inherent properties appearing in a speckle image and the object in this image is readily corrupted by the speckle information. Speckle is a common phenomenon in ultrasound imaging systems. It comes from coherent interference of scatterers and it appears as a granular structure superimposed on the image. Speckle is an artifact degrading target visibility and limits the ability to detect lower contrast lesions in ultrasonic imaging. Since segmentation of lesion delineation is not easy by using a simple thresholding method, an adaptive thresholding method was designed for converting a gray speckle-type ultrasound image to a useful binary image in our proposed algorithm, which would be helpful for the further extraction of significant objects from the ultrasound image.

To highlight the hypoechoic (i.e., lesion) region in the ultrasound image, the threshold for binary image generation must be selected adaptively. In this study, the ratio of mean gray-scale value within whole ultrasound image and within a local region of interest (ROI) is adopted to individually adjust the binary threshold value. If the ratio was greater than 1, it means the characteristic of ROI tending to lesion and thus, the binary thresholding value should be assigned to higher value. Since the ratio can be viewed as an index to distinguish the characteristic of each local ROI within the whole ultrasound image, it can be used as a weighting factor to adjust binary thresholding value.
Figure 2(a) gives an example with 8-bit simulated image containing one irregular-type lesion with signal to noise ratio (SNR) of 20 dB. The image is denoted by a 2-D matrix $G$ with the size of $256 \times 256$ pixels. The mean brightness in gray-scale of Fig. 2 (a) is 178. Figure 2(b) illustrates the cumulative distribution function (CDF) of three manually selected ROIs (white square boxes in Fig. 2(a)) with the size of $8 \times 8$ indicating respectively the speckle (ROI 1), lesion edge (ROI 2), and lesion (ROI 3) regions, respectively. As shown in Fig. 2(b), the CDF rising rate of lesion region (solid line) is greater than that of either lesion edge (dashed line) or speckle region (dashed-dot line).

A binary threshold value is essential to roughly separating the lesion, lesion edge, and speckle background three regions. Selecting the appropriate threshold is important, since variations of speckle noise will influence the results of binary transformation if the binary threshold is either too high or too low. In this study the threshold value was determined by analyzing a series of simulation data with signal-to-noise ratios (SNRs) ranging from 10 to 30 dB. For the results presented here we used a binary threshold as the product of the gray-level of 30% corresponding CDF and the weighting factor, which provided the reasonable transformation of binary images under different SNR conditions. Note that the CDF and weighting factor two quantities are uncorrelated.
In Fig. 2(b), the three selected ROIs gray level thresholds (denoted by circle symbols) are 154, 132 and 157, respectively. The pixels within the ROI below the gray level threshold are assigned to be a black pixel. The adaptive thresholding procedure is executed until the entire original image is transformed to a binary image. Note that to obtain an entire binary image from the original one, the process has to array multiple ROIs to cover the entire image. The ROIs with the size of 8×8 pixels were arrayed adjacent to each other with 87.5% overlap. Figure 2(c) shows the obtained binary image as a matrix $B$ after performing the adaptive thresholding procedure.

2.2. Extract Significant Object Using Disk Expansion Scheme

Theoretically, this segmentation work can also be done by the morphological method using close and open operations. Although the close and open operations are strongly dependent on the structuring element, e.g., a $3 \times 3$ square array, for the fast computation, the iterations of closing and opening are generally decided in heuristic. This is because the a priori knowledge of noise involved in an image is usually unknown. To overcome this problem, the classical concept of maximal disk, which is well-known for the computation of skeletons instead of the use of structuring element is adopted in the disk expansion method.
Disk expansion scheme is a preprocessing of finding the key position of the object. Only black pixels would be verified by the disk expansion scheme since the black pixel has a higher possibility of belonging to the part of lesion region, whereas the white pixel tends to the speckle background. Consider a black pixel \( B(x, y) \) as the disk expansion center and assign a starting disk with radius \( r = 1 \) to check whether the inside of the disk exists a white pixel or not. If not, increasing the disk radius \( r \) until a white pixel is found. After disk expansion processing all the black pixels, a radius-based matrix \( R \) (the same dimension as \( B \)) can be obtained, where each black pixel \( B(x, y) \) corresponds to a positive radius value \( R(x, y) \). Let the maximum radius value be denoted by \( r_{\text{max}} = \max_{y} r \). The key position of the object can be defined at the location \((x_{\text{max}}, y_{\text{max}})\) with \( r_{\text{max}} \), that is, \( R(x_{\text{max}}, y_{\text{max}}) = r_{\text{max}} \).

Even the matrix \( R \) may show the appearance of the significant lesion region in the ultrasound image, it still can not be used due to the need of accurately detecting lesion’s contour. Hence a further detection process for obtaining the significant object is required. Based on the statistical property displayed in the binary image, a CDF method is used to filter out the most insignificant pixels. Let \( N \) be the total number of black pixels in \( B \), and \( \text{cdf}(r) \), \( r = 1, \ldots, r_{\text{max}} \), be the cumulative distribution function
for all \( r \), then a threshold controlled by the percentile \( p = 0, \ldots, 100\% \) is defined as follows.

\[
TH_p = \{ r \mid cdf(r) \approx pN \}
\]  

(1)

where \( p \) is empirically determined and usually depends on ultrasound image characteristics such as the size of detected objects. If the object’s size is larger, the increasing trend of \( cdf(r) \) will be faster along \( r \)-axis and selecting a lower \( p \) is suitable for extracting the object. Otherwise, for the smaller size of object, a higher \( p \) may be used. In our experiments, typical value from 0.5 to 0.7 is suggested. Thus for a percentile \( p \) selected by a specific application, with the thresholding value \( TH_p \) the \( R \) can be converted to a label matrix \( L \) as follows for extracting the possible objects.

\[
L(x, y) = \begin{cases} 
1 & \text{if } R(x, y) > TH_p \\
0 & \text{otherwise}
\end{cases}
\]  

(2)

Here “1” and “0” are treated as a label for further processing.

The “1” pixels in \( L \) may be composed of several objects of interest. In addition, the region of the most significant object has to include the location \( R(x_{\text{max}}, y_{\text{max}}) = r_{\text{max}} \). Hence we put a label, say “2”, for the coordinate \( (x_{\text{max}}, y_{\text{max}}) \) in \( L \). To effectively extract the most significant object, based on the label “2”, an iterative operation is performed for finding all of the pixels connected to this label.
For each “1” in \( L \), if its neighbor exists a “2”, then “2” is used to replace the “1”. This process is performed iteratively until not any “1” is changed. With the current radius information in \( R \), let all elements in \( L \) be updated by the following expression.

\[
L(x, y) = \begin{cases} 
2 & \text{if } (x, y) \in \text{any disk having nonzero } r \\
0 & \text{otherwise}
\end{cases} 
\]  

(3)

After this process, the most significant object is extracted based on the region with “2” labels in \( L \). Note that all the elements in \( R \) with respect to non-“2” labels in \( L \) are reset to 0. Figure 2(d) illustrates the result after this stage, where each radius value in \( R \) is displayed with a normalization into gray range (0~255) for visualization. In the current example, the percentile \( p = 70\% \) is used in (1) and (2), and the coordinate (124, 139) having the maximum radius 16 is found and plotted with a white-cross mark.

In order to eliminate some small holes in this region, morphological operations, dilation and erosion, are suggested and applied on \( L \). In our algorithm, we performed dilation following erosion two times on the image for eliminating small holes, where the structuring element is with a size of \( 3 \times 3 \). Thereafter, the most significant object in \( G \) can be extracted based on the “2” region in \( L \) as shown in Fig. 2(e).

2.3. Refine the Extracted Object
In addition to the significant region located, the contour of the lesion detection is also of great importance. However, due to speckle noise effect and the original “1” labels in L determined by $\text{TH}_p$, it is possible that some pixels are misclassified. Therefore, referred to the “2” region in L, the original gray image G is involved in this stage to refine the extracted object. Let $A_2$ be the “2” region representing the previously extracted significant object in L. Within the same region $A_2$ in G, we compute the mean object’s gray value $\overline{g}_{\text{object}}$ as follows.

$\overline{g}_{\text{object}} = \frac{1}{N_{A_2}} \left[ \sum_{(x,y) \in A_2} G(x,y) \right], \quad (4)$

where $N_{A_2}$ represents the total number of pixels in $A_2$. In the current case of Fig. 2(e), $\overline{g}_{\text{object}} = 96$.

Further, since some pixels outside $A_2$ may belong to the object’s ones and some pixels in $A_2$ may belong to the non-object’s ones, we dilate several times (typical 10 to 12 times, which are empirically determined according to the contrast between object and background. The higher the contrast is, the less the dilation times are.) for the $A_2$ region to obtain an outer band region denoted as $A_3$ which does not include $A_2$. All the pixels of $A_3$ in L are labeled by “3”. Because the most pixels in $A_3$ belong to the background pixels, we compute the mean background’s
gray value \( \overline{G}_{\text{background}} \) by the following expression.

\[
\overline{G}_{\text{background}} = \frac{1}{N_{A3}} \left[ \sum_{(x,y) \in A3} G(x, y) \right],
\]

(5)

where \( N_{A3} \) represents the total number of pixels in \( A3 \). After performing such a dilation process on Fig. 2(e), the outer band region \( A3 \) is obtained as shown in Fig. 2(f), where \( \overline{G}_{\text{background}} = 179 \).

Based on \( \overline{G}_{\text{object}} \) and \( \overline{G}_{\text{background}} \), for the gray image \( G \), we test all pixels in the region of \( A2 \cup A3 \) provided by the labeling matrix \( L \). If the gray value of a pixel is near to \( \overline{G}_{\text{object}} \), we classify it as an object pixel, otherwise a background pixel. The region of the refined significant object is recorded in an object matrix \( O \) and can be formulated by the following expression, where “1” part denotes the region of the final extracted object and “0” denotes the background.

\[
O(x, y) = \begin{cases} 
1 & \text{if } (x, y) \in A2 \cup A3 \text{ and } G(x, y) - \overline{G}_{\text{object}} < |G(x, y) - \overline{G}_{\text{background}}| \\
0 & \text{otherwise}
\end{cases}
\]

(6)

Once of dilation and erosion operations are performed after \( O \) is obtained in order for eliminating some singular points which may be a “0” pixel or a “1” pixel. Let \( O \) be regarded as a binary image, and the disk expansion for the significant object extraction is reperformed with \( p = 0 \), referred to path (2) in Fig. 1. After the second
round, the refined result is obtained. The object’s contour can be easily marked from the finally found region of the most significant object as Fig. 2(g) shows.

2.4. Extract Multiple Objects

The proposed algorithm can be easily extended for the extraction of multiple objects. If there are several regions of lesions appearing in an ultrasound image, our algorithm can extract sequentially the lesions of interest starting from the lesion with the largest size. The iterative scheme for this purpose is designed as follows. Based on the procedure of the proposed algorithm, once the largest lesion’s region is extracted, we remove this region from B. Bypass the step of adaptive thresholding and perform the other steps as introduced previously, we can extract the second largest region of lesions. This process is iteratively performed until the wanted number of lesions to be extracted is achieved.

According to the above description of the proposed approach, our proposed algorithm can be summarized as follows.

**Semi-Automatic Contour Extraction Algorithm of Ultrasonic Breast Lesions**

1. Select $p$ value for the first round for object extraction. Typical value is from 0.5 to 0.7 and depends on ultrasound image quality.
2 Select the number of objects wanted to be extracted.

3 Input a gray ultrasonic image $G$.

4 Perform the adaptive thresholding to obtain a binary image $B$.

5 Extract the significant object (some morphological operations are included).
   
   5.1 Perform the disk expansion process to obtain the radius matrix $R$ and find the key position $(x_{\text{max}}, y_{\text{max}})$ in $R$ such that $R(x_{\text{max}}, y_{\text{max}}) = r_{\text{max}}$.

   5.2 Use (1) and (2) to derive the label matrix $L$.

   5.3 Use (3) to update $L$.

   5.4 Extract the most significant object in $G$ based on the “2” region in $L$.

6 Refine the extracted object (some morphological operations are included).

   6.1 Use (4) to compute $\bar{g}_{\text{object}}$ in region $A2$.

   6.2 Use (5) to compute $\bar{g}_{\text{background}}$ in region $A3$.

   6.3 Use (6) to obtain the object matrix $O$.

   6.4 Regard $O$ as a binary image and reperform steps 5 and 6 with $p = 0$ (the second round) to find the finally refined object.

7 Remove the part of the extracted object from $B$, and do steps 5 and 6 for next object extraction until all the desired objects are contoured.

3. RESULTS AND DISCUSSION
3.1. Simulation Results

To evaluate the performance of the proposed algorithm, simulated images of varying types of cysts with different contours were used [23]. For emulating speckle characteristic, the backscattered amplitude from each scatterer is random, and the scatterers have an independent and identical distribution in 2-D space. The center frequency of transducer was 5 MHz. The cysts with varying shapes were also embedded in speckle background with SNR of 20 dB. According to the classification of contours of breast lesions proposed by Chou et al [9], seven types of cysts were designed to describe the benignancy and malignancy of lesions. In addition to the irregular type illustrated in Fig. 2, other six types of cysts including smooth, macro-lobuate, micro-lobuate, pseudo-pod, zigzag, and speculate shown in Figs. 3(a) are also adopted in our experimentation. Figures 3(b) represents the simulated images. The contour extraction results obtained by our algorithm are shown in Figs. 3(c), where the white color contours represent the boundary of lesions and demonstrate the feasibility of our approach.

The boundary error and estimation area error between the simulated contours and the delineations obtained by the proposed algorithm were used for further evaluations [13]. The boundary error is defined as the mean shortest distance between the
simulated contour and our algorithm’s delineation. We denote the simulated contour boundary as \( M = \{ m_1, m_2, \ldots, m_n \} \) and the result obtained by our algorithm as \( P = \{ p_1, p_2, \ldots, p_m \} \), where each element of \( M \) or \( P \) is a point on the corresponding contour. We find the distance of every point in \( P \) from all points in \( M \), and define the distance to the closest point for \( p_j \ (\forall p_j \in P) \) to the contour \( M \) as

\[
d(p_j, M) = \min_w \| p_j - m_w \|
\]  

(7)

where \( \| \| \) is the 2-D Euclidean distance between any two points. Then, all the \( d \) values are calculated to obtain the statistics of mean, minimum, and maximum values.

The area error is represented by the three parameters including true positive (TP), false negative (FN) and false positive (FP). They are defined as follows.

\[
TP(\%) = \frac{| A_s \cap A_p |}{| A_s |}
\]  

(8)

\[
FN(\%) = \frac{| A_s \cup A_p - A_p |}{| A_s |}
\]  

(9)

\[
FP(\%) = \frac{| A_s \cup A_p - A_s |}{| A_s |}
\]  

(10)

where \( A_s \) refers to the region of the lesion as determined by simulated contour, \( A_p \) is the region of the lesion determined by our algorithm, and operator \( | \| \) is
defined as the transformation from region to area value. The three measures were used to find the differences between the simulated contour and the contour obtained by our algorithm as illustrated in Fig. 4.

To test the performance of the proposed algorithm under different image qualities, we also used the simulated ultrasound images with SNRs ranging from 10 to 30 dB. The images of each cyst type were tested and the statistic analyses are shown in Fig. 5. Figures 5(a)-(c) represent the $TP$, $FN$ and $FP$ estimates, respectively. The results reveal that the mean normalized $TP$ area overlap in all simulated images is over 85%. The mean normalized $FN$ is lower than 15% and the mean normalized $FP$ is lower than 16% due to the boundary discrepancies from speckle noise interference. The mean shortest distance error between simulated contours and contours obtained by the proposed algorithm is 1.3 pixels. The standard deviation and maximum value results are 3.2 and 18.8 pixels, respectively.

3.2. Phantom Data Analysis

A custom-made phantom (Department of Medical Physics, University of Wisconsin-Madison, WI, USA) containing a variety of image objects with differing physical properties was used to experimentally investigate the performance of the proposed algorithm [24]. A programmable digital array system (DiPhAS, Fraunhofer
IBMT, Ingbert, Germany) with a 5.57 MHz linear array (L6, STI, State College, PA) of 128 channels was used to acquire the phantom images [25].

Figure 6(a) shows the irregular tumor pattern image; and the B-mode contrast relative to glandular background tissue is -10 dB. The image size is 201×199 pixels. Figure 6(c) shows the image comprising a background of glandular material with three different contrast spheres with a radius of 4 mm. The upper-right, upper-left and lowest sides are the cyst, high-attenuation pattern, and fat sphere; and their B-mode contrasts relative to glandular background tissue are -14 dB, -12 dB and -14 dB, respectively. The contour extraction results in white solid lines as shown in Figs. 6(b) and (d) demonstrate the superior performance of the proposed algorithm. In the two cases, the mean normalized $TP$ area overlap is over 85%. The mean normalized $FN$ is lower than 12% and the mean normalized $FP$ is lower than 5%. The mean shortest distance error between actual phantom image contours and contours obtained by the proposed algorithm is 3 pixels. The standard deviation and maximum value results are 4.5 and 7.2 pixels, respectively.

3.3. Clinical Data Analysis

The clinical breast images were also used to test the proposed algorithm. The images were acquired using a commercial imaging system (ATL HDI 5000, Bothell,
Washington, U.S.A.) and a linear array transducer (ATL L12-5, 50 mm, Bothell, Washington, U.S.A.) at National Taiwan University Hospital. Each pixel in the acquired image had a resolution of 8 bits. The original breast images are shown in Figs. 7(a), where the white dotted-line boxes indicate the selected ROIs being transferred to binary images prior to the contouring process. The contour results obtained by the proposed algorithm are shown in Figs. 7(b). The manual delineations by an experienced physician are shown in Figs. 7(c). There are high correlations between the physician manual contours and the contours obtained by our algorithm. The mean normalized TP area overlap is over 90%. The mean normalized FN is lower than 5% and the mean normalized FP is 10%. The mean shortest distance error between the physician manual contours and contours obtained by the proposed algorithm is 8.5 pixels. The standard deviation and maximum value results are 10.5 and 15.2 pixels, respectively. The result of multiple lesions extraction shown in Fig. 8 obtained by the propose algorithm further confirms the effectiveness of the proposed approach.

We also invited ten experienced physicians to manually contour the lesion boundaries in other six clinical breast images and then compared the results with our proposed method did. The statistic analyses between the ten physicians’ manual delineations and detected contours by our proposed method are shown in Figs. 9. The
symbols from “A” to “J” in lateral axis represent the physicians’ order. Note that since there is no ground truth of the ten physicians’ manual delineations, the contour results by our proposed method and physicians’ manual delineations were designated as the terms of $A_s$ and $A_p$ in Eqs. (8)-(10), respectively. In other words, there were six independent estimates of $TP$, $FN$, $FP$ and shortest distance in each physician’s manual delineations. The mean shortest distance error between the physician manual contours and contours obtained by the proposed algorithm is 1.4 pixels. The standard deviation and maximum value results are 11 and 17 pixels, respectively.

Figures 9(a)-(d) show the results of $TP$, $FN$, $FP$ and shortest distance estimates, respectively. The results show that a strong correlation (mean $TP > 0.9$) exists between the ten physicians’ manual delineations and detected contours in clinical breast images. Note that the $FP$ estimates in Fig. 9(c) have larger values. The main reason is that manual contours always cover additional area due to the boundary discrepancies from speckle noise interference.

The receiver operating characteristic (ROC) distribution was also used in clinical data analysis. Since there is no ground truth of the ten physicians’ manual delineations, the ROC can be represented equivalently by plotting the $TP$ versus $FP$ estimates. There were totally 60 $TP$ versus $FP$ discrete estimates.
since ten physicians’ manual delineations in six clinical images. The ROC
distribution is shown in Fig. 10. The proposed method yielded estimates in the
upper left corner of the ROC space. In other words, the proposed method
provided high sensitivity and specificity for contouring the lesion boundary.

3.4. Comparisons with GVF-Snake Method

Two simulated images with irregular and spiculate cysts, and three clinical
images from Figs. 7 (a) were used to test the performance of GVF snake algorithm.
Obviously, the GVF snake algorithm contour results as shown in Figs. 11 can not
perform very well. The main reason is that the variations of speckle noise affect the
energy computation and convergence trends. The mean normalized $TP$, $FN$ and $FP$
values between the physician manual contours and the contours obtained GVF
snake algorithm are 81%, 19% and 9%, respectively. The mean shortest
distance error is 13.2 pixels. The standard deviation and maximum value results
are 12.5 and 17.6 pixels, respectively.

4. CONCLUDING REMARKS

In this study, we present an effective segmentation method to find lesion
contours in ultrasonic breast images on the simulated, in-vitro phantom and
clinical images. Since the proposed method converted the original ultrasound
image into a binary image, the ultrasound image embedding speckle noises can be regarded as degraded paint characters image containing closure noise. Then, an iterative disk expansion scheme was adopted to remove the closure noise. In other words, the proposed method suffers less variations of speckle noise. The simulation results show that the mean normalized true positive area overlap between simulated contour and contour obtained by the proposed algorithm is over 85% and the mean shortest distance is below 1.5 pixels. There are high correlations between ten experienced physicians’ manual contours and the contours obtained by the proposed method in clinical breast images. The proposed approach has also been verified to be able to simultaneously contour multiple lesions in a single image.

In comparison to the contours obtained from GVF snake algorithm, the proposed method needs not position any initial seed point within the lesion; and it can thus be viewed as a semi-automatic process. In addition, the GVF snake algorithm contour results in Figs. 11 do not perform well in both simulations and clinical images. Since the running time for contour extraction in a single breast lesion image was 0.06 s on a 3.0-GHz Intel Xeon machine, the proposed algorithm is feasible to be implemented in a real-time ultrasound imaging system. Even though our proposed method has several heuristics, this paper provides
another feasible direction for detecting the ultrasonic breast lesions. The reduction of heuristics will be a good topic for further study.

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For the next significant object extraction
Removal of the part of the extracted object from B

Fig. 1: Flowchart of the proposed approach. Path (1) performs the primary object extraction task, whereas path (2) is used for rechecking and extracting the final result. The left path provides the original binary image and is used for removing the extracted objects. Along the feedback path at right, the multiple significant objects can be extracted consequently.
Fig. 2: (a) A simulated ultrasound image $G$ with the size 256×256. The three ROIs represent the speckle (ROI 1), lesion edge (ROI 2), and lesion (ROI 3) regions, respectively. (b) The CDF rising rate of lesion region (solid line) is larger than that of either lesion edge (dashed line) or speckle region (dashed-dot line). (c) The obtained binary image $B$ after applying the adaptive thresholding process. (d) The radius information $R$ converted into gray range (0~255) for visualization, where the coordinate (124, 139) having the maximum radius 16 is plotted with a white-cross mark. (e) The corresponding gray information under the region $A_2$ of the extracted significant object, where $\bar{G}_{\text{object}} = 96$. (f) The outer band region $A_3$ displayed with the gray information, where $\bar{G}_{\text{background}} = 179$. (g) The finally found region, where the contour of the lesion is plotted with a white curve on $G$. 
**Fig. 3:** (a) Simulation cyst patterns, (b) simulated ultrasound images, and (c) the detected contours (indicated by white lines) by the proposed method.
Fig. 4: Illustrations of the area error parameters including true positive ($TP$) region (as oblique lines), false negative ($FN$) region (as vertical lines) and false positive ($FP$) region (as horizontal lines).
Fig. 5: Statistic analyses of detected contours are shown in (a) true positive (TP), (b) false negative (FN), (c) false positive (FP), and (d) shortest distance estimates and their standard deviations. The simulated images of seven cyst types with different SNRs ranging from 10 to 30 dB were tested.
Fig. 6: Phantom images. (a) and (c): original images. (b) and (d): detected contours by the proposed method.
Fig. 7: Three clinical images analysis. (a) Original images, (b) detected contours by the proposed method, and (c) physician’s manual delineations.
**Fig. 8:** Clinical image analysis in multiple-lesion contours. (a) Original image and (b) detected multiple-lesion contours by the proposed method.
Fig. 9: Ten physicians were invited to manually contour the lesions of six clinical breast images. The statistic analyses between the ten physicians’ manual delineations and detected contours by our proposed method are shown in (a) true positive ($TP$), (b) false negative ($FN$), (c) false positive ($FP$), and (d) shortest distance estimates and their standard deviations.
**Fig. 10:** Receiver operating characteristic (ROC): Relationship between true positives \((TP)\) versus false positives \((FP)\) in clinical images.
Fig. 11: Contours results from gradient vector flow (GVF) snake algorithm in simulated images with (a) irregular- and (b) spiculate-cyst patterns and (c)-(e) clinical images from Figs. 7(a).