Strain Compounding: Improvement in Contour Extraction of Ultrasonic Breast Imaging

Wei-Ning Lee  Pai-Chi Li*

Department of Electrical Engineering, National Taiwan University, Taipei, Taiwan, 114, ROC

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Abstract

Computer-aided diagnosis for breast diseases has gained wide interest. In ultrasound, the automatic diagnosis typically requires knowledge of the shape of a lesion, thus making contour extraction a critical step. Unfortunately, the speckle noise inherent in an ultrasonic image not only lowers the contrast resolution but also limits the accuracy of contour extraction. Thus, speckle noise reduction is desired prior to contour extraction. Contour extraction with a speckle noise reduction technique called strain compounding is presented in this paper. Strain compounding reduces speckle noise by incoherently combining partially correlated measurements of the same image object. Efficacy of speckle reduction using strain compounding has been demonstrated on both simulated and clinical images under different strain conditions. It was shown that speckle noise can be effectively reduced without significant degradation in spatial resolution. In this paper, we further demonstrate its ability to improve accuracy of contour extraction. Simulations and clinical images are both included and the improvement is also quantified and discussed.

Keywords: Computer aided diagnosis, Contour extraction, Strain compounding, Ultrasonic imaging

Introduction

The occurrence of breast cancer, which is the main cause of death for females, has been increasing recently. Ultrasound has become a popular tool for early diagnosis due to its non-invasiveness and ease of operation. However, the speckle brightness variations inherent in ultrasonic imaging limit the detection of low contrast lesions. In addition, the interpretation of the shape and the size of a lesion, as well as the subsequent diagnosis, is subjective. This may lead to unnecessary follow-up operations such as biopsy and fine needle aspiration. Thus, a Computer-Aided Diagnosis (CAD) system for the detection of breast cancer is desired to provide objective and accurate interpretation and to avoid unnecessary operations.

CAD provides diagnostic information to doctors based on computerized analysis from an image. For ultrasonic breast imaging, it consists of two steps. One is to identify the lesion location by contour extraction and the other is to classify the lesion as benign or malignant. Previous research works primarily focused on lesion classification with manual contour extraction [1-3]. Automatic contour extraction has not been successful partly due to the interference from the speckle noise. Hence, it is of particular research interest to investigate the use of speckle noise reduction in improving automatic contour extraction.

To reduce speckle brightness variations, compounding techniques, including spatial compounding and frequency compounding, have long been investigated [4-11]. The primary hypothesis of compounding is that the ensemble average of a speckle image is the same as the incoherent average of the original object. Therefore, by incoherently averaging partially correlated measurements, speckle brightness variations can be reduced without affecting the original image contrast. The improvement, however, is gained at the expense of spatial resolution.

In this paper, the strain compounding technique [12-13] is used to reduce speckle noise. It potentially can achieve the same level of speckle noise reduction, with less degradation in spatial resolution if a large compression can be applied. With strain compounding, contour extraction of lesions is further done by the GVF-snake algorithm [14]. Both simulated images with cysts and clinical images with lesions are used. The extracted contours of original images are finally compared to those of compound images to evaluate the effects of strain compounding on contour extraction.

Materials and Methods

Strain compounding

Strain compounding was proposed by Li and Chen [12].
Further study of strain compounding on human images has been previously tested [13]. Performance of speckle reduction was tested based on 2-D speckle tracking using postdetection images. 2-D speckle tracking involved in strain compounding process is performed to correct for tissue motion resulting from external compression and to ensure that the images to be compounded are spatially matched. A more efficient speckle tracking algorithm was used in strain compounding for real-time or near-real-time implementation [18]. The compounding processing time was significantly reduced by using the efficient speckle tracking method and reduction of speckle brightness variations on clinical breast imaging was also demonstrated in Figure 2.

Contour extraction

Contours of the compound image were extracted by Gradient Vector Flow for Snake (GVF-snake) algorithm [14]. This algorithm utilizes a new external force for active contours and is less affected by the problems associated with initialization and poor convergence to boundary concavities. This external force, which is known as the gradient vector flow, is computed as a diffusion of the gradient vectors of a gray-level or binary edge map derived from the image. In addition, GVF-snake software is available to the public at http://iacl.ece.jhu.edu/projects/gvf.

A traditional snake is a curve, \( x(s) = [x(s), y(s)], s \in [0,1] \) that moves through the spatial domain of an image in order to minimize the energy function \( E \)

\[
E = \int_{
\frac{1}{2}} \left[ \alpha \left| \nabla x'(s) \right|^2 + \beta \left| \nabla y'(s) \right|^2 \right] + E_{\text{ext}}(x(s))ds, \quad (1)
\]

where \( \alpha \) and \( \beta \) are weighting parameters that control the snake’s tension and rigidity, respectively, and \( x'(s) \) and \( y'(s) \) denote the first and second derivatives of \( x(s) \) with respect to \( s \). The external energy function \( E_{\text{ext}} \) is derived from the image so that it takes on smaller values at the features of interest, such as boundaries. The overall GVF-snake approach is to use the force balance condition (2) as a starting point for designing a snake.
Strain Compounding and Contour Extraction

Start

Read image $I(x,y)$

Compute edge map $f(x,y)$

Define GVF field: $F_{\text{ext}}^{(x)} = V(x,y) = \left[u(x,y), v(x,y)\right]$, which minimize

$$E = \int \mu(u_{x}^{2} + u_{y}^{2} + v_{x}^{2} + v_{y}^{2}) + \kappa f^{2} - |V| dxdy$$

Solve

$$\mu \nabla^{2} u - (u - f_{x})(f_{x}^{2} + f_{y}^{2}) = 0$$

$$\mu \nabla^{2} v - (v - f_{y})(f_{x}^{2} + f_{y}^{2}) = 0$$

Obtain

$$u(x,y,t) = \mu \nabla^{2} u(x,y,t) - \left[u(x,y,t) - f_{x}(x,y)\right] \left[f_{x}(x,y)^{2} + f_{y}(x,y)^{2}\right]$$

$$v(x,y,t) = \mu \nabla^{2} v(x,y,t) - \left[v(x,y,t) - f_{y}(x,y)\right] \left[f_{x}(x,y)^{2} + f_{y}(x,y)^{2}\right]$$

Get $V$

Solve dynamic snake equation:

$$x_{s}(s,t) = \alpha x^{+}(s,t) - \beta x^{-}(s,t) + V$$

End

Figure 3. Flow chart of GVF-snake.

(a) Smooth

(b) Pseudo-pod

Figure 4. Simulated contour (left), simulated image (middle) and the compound image (right).

$$x_{s}(s,t) = \alpha x^{+}(s,t) - \beta x^{-}(s,t) + V .$$

The curve solving the above dynamic equation is a GVF snake. It is solved numerically via discretization and iteration. The flow chart of the GVF-snake algorithm is shown in Figure 3.

Simulation

Simulations are performed to evaluate the performance of the above mentioned contour extraction technique with and without compounding. Several types of cysts with different contours are simulated with speckle characteristics. The simulation model is based on that proposed by Li and Wu [13]. According to this model, scatterers are randomly distributed in a 3-D space. The amplitude of the echo from each scatterer is random, and all scatterers have an independent and identical distribution. The phase of the echo, on the other hand, changes with the distance between the scatterer and the transducer. The minimum spacing between two possible scatterer positions is 0.02 mm. The point spread function (PSF) of the imaging system is a cosine-modulated 3-D Gaussian function:

$$PSF(x,y,z) = e^{-x \left(\frac{a^{2}}{a_{x}^{2}} + \frac{b^{2}}{a_{y}^{2}} + \frac{c^{2}}{a_{z}^{2}}\right) \cos(2\pi f_{0}z)}.$$
envelope of the predetection signal is computed at a certain elevational position (i.e., the image plane) using the Hilbert transform. Using this model, 3-D tissue motion can also be simulated by moving the original position of a scatterer to a new position.

In order to test if strain compounding is beneficial to contour extraction, a series of cysts with various shapes were emulated. These cysts were also embedded in speckle background. Through the simulated images with cysts, differences between simulated contours and the extracted contours based on original and compound images can be compared. According to the classification of contours of breast lesions proposed by Chiang et al. [1], there are seven types of shapes to describe the benignancy and malignancy of lesions. In this paper, two of the seven contours, smooth and pseudo-pod were shown.

Two sets of simulated images with a size of 5.12×5.12 mm and the corresponding compound images are shown in Figure 4. Figure 4 (a) and (b) show smooth contour and pseudo-pod contour, respectively. Note that the compound image was obtained from five partially correlated original images and the speckle noise was reduced by up to 40%.

Results

Performance of contour extraction was tested on the simulated images shown in Figure 4. Both the boundary error and the area error between the real contours and the GVF-snake results were compared. The boundary error is defined as the shortest path between the real contour and the GVF-snake delineation, while the area error is represented by the following three parameters. They are true positive (TP), false negative (FN) and false positive (FP) [19]. The three measures were used to find the difference between the simulated contour and the contour obtained from the GVF-snake. The parameters are also illustrated in Figure 5.

Figure 6 shows the results of contour extraction on the simulated images. From the shortest paths and the area errors shown in Table 1, the accuracy of the delineation based on the compound images is higher than that based on the original images. Compounding improves the accuracy of automatic contour extraction in these cases.

The clinical breast images shown in Figure 7 were also used to test automatic contour extraction. The images were
Strain Compounding and Contour Extraction

(a)  
(b)  
(c)  
(d)  

Figure 7. Results of contour extraction on clinical breast images, including original images ((a) - (c)) and compound images ((b) - (d)).

Table 1. The shortest path and area error values between the simulated contour and the extracted contour from both the original and the compound images.

<table>
<thead>
<tr>
<th>Smooth</th>
<th>Shortest Path</th>
<th>Area</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std</td>
</tr>
<tr>
<td>Original</td>
<td>2.77</td>
<td>1.92</td>
</tr>
<tr>
<td>Compound</td>
<td>2.80</td>
<td>1.53</td>
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<table>
<thead>
<tr>
<th>Pseudo-pod</th>
<th>Shortest Path</th>
<th>Area</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std</td>
</tr>
<tr>
<td>Original</td>
<td>2.93</td>
<td>2.34</td>
</tr>
<tr>
<td>Compound</td>
<td>1.76</td>
<td>1.12</td>
</tr>
</tbody>
</table>

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.). During image acquisition, the breast was axially compressed by a transducer held by a clinical technician in order to create different strain states required by the strain compounding method. Each pixel in the acquired image had a resolution of 8 bits, and the total image is 240×352 pixels. Images in the left and right columns are the GVF-snake results based on the original and the compound images respectively. Performance of contour extraction on clinical breast images was evaluated by two experienced physicians. It is concluded that automatic contour extraction potentially benefits from the compound images.

Discussions and Conclusions

This study tested the performance of strain compounding in improving automatic contour extraction on both simulated and clinical images. Results show that compounding improves accuracy of automatic contour extraction of lesions and thus may be beneficial to breast CAD in ultrasound.

For the simulated images, accuracy of contour extraction on simulated images can be determined since the true contours are known. On the contrary, the real boundaries and areas of breast lesions in clinical images are unknown. Thus, accuracy of the extracted contours in clinical breast images still depends on the diagnoses of experienced physicians. Moreover, breast lesions are complicated in that the interior of a lesion is often
not homogeneous. Particularly for a malignant lesion, there may exist bright spots and these spots do not have speckle characteristics. Thus, they may be regarded as boundaries during boundary extraction and affect the accuracy of the GVF-snake method. Alternative contour extraction methods that can provide more accurate results are a focus of on-going research.

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References


