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A DISCRETE REGION COMPETITION APPROACH INCORPORATING WEAK EDGE ENHANCEMENT FOR ULTRASOUND IMAGE SEGMENTATION

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ABSTRACT

Ultrasound images are difficult for analysis due to their complex textures and speckle noises. Taking into account these two characters, in this paper, we present a new region-based approach for ultrasound image segmentation. The proposed approach is composed of two primary algorithms, namely, discrete region competition and weak edge enhancement. The discrete region competition features four techniques, i.e., region competition, statistics modeling, early vision modeling, and discrete concept. To prevent a region from flooding out of the desired area, weak edges located on the slowly varying slope are enhanced according to their position on the slope and the length of the slope. The discrete region competition incorporating weak edge enhancement has been verified on clinical ultrasound images and promising results have been achieved.

I. INTRODUCTION

Region-based techniques are frequently used for image segmentation. The basic idea of most region-based approaches is to bring together adjacent pixels with similar characteristics according to user-specified criteria. More specifically, a region-based approach is usually composed of two essential components. One component is the mechanism to gather adjacent pixels to form regions and the other component is the criteria used to determine the set of pixels, which may form a region. Typical mechanisms are region growing and spilt-and-merge. Typical criteria are the gray-level difference of two adjacent pixels or regions and the Euclidean distance between the feature vectors associated with two adjacent pixels or regions.

Even though region-based approaches have been well studied and successfully applied to those images with a good quality, the classic techniques can easily fail in segmentation of ultrasound images due to three problems inherent in an ultrasound image. One of these three problems is the texture reflecting the tissue properties. Another is the speckle noise generally existing in ultrasound images as a result of coherent interference of backscattered echoes. The other is the weak edge on the desired boundary, which may be either due to the artifacts or caused by a similar acoustic property between two adjacent tissues. While the first two, i.e., textures and speckle noises, may form false edges, the last may lead to missing edges on the desired boundary.

To cope with the first two problems, in this paper, we propose a new region-based approach, namely, discrete region competition, for ultrasound image segmentation. Region competition was originally proposed by Zhu and Yuille [1], which is basically a region-based method that considers a global energy combining the log likelihood term and the penalty term of arc length. This approach models all regions and backgrounds by the log-likelihoods. The parameters of the log-likelihoods in every region are estimated by the maximum likelihood estimates. The regions then grow along the steepest descent direction of the global energy function by the likelihood ratio tests of regions and backgrounds. When the regions meet at a common boundary, the pixels move according to the competition of log-likelihoods, that is, the likelihood ratio tests.

Region competition has been shown to be effective in many image segmentation problems. However, it does not performed well on ultrasound images due to the interference of the tissue-related textures and the speckle noises. To improve the intrinsic problems of region competition, the proposed discrete region competition approach combines the advantages of the region competition, the statistical modeling of speckles, the early vision model, and the *discrete* concept for ultrasound image segmentation. The statistical modeling is to account for the statistical property of speckle noises in an ultrasound image more accurately. Rather than modeling the image by a Gaussian distribution, a Rayleigh distribution or its transformation is employed for speckles [2] in the proposed algorithm.

The early vision model is to generate the edge information between different textures in an ultrasound image. By mimicking human visual perception, it has been shown that the early vision model [3-4] proposed in one of our recent works may highlight edge information while the speckles are suppressed. The advantage of using the early vision model over the conventional edge detectors is that it not only can find the edges between two uniform regions with different gray levels but also can identify the edges between two regions with different textures.

The *discrete* concept was first proposed for the snake model [5] to overcome the local minima resulted from the textures, speckles and artifacts. The idea is to move the boundary points of each region over the peaks on the distance map, which is the result of the early vision model [3-4]. The rationale behind this idea is in two folds. One is that it promises a more accurate boundary for each region since the peaks of distance map provide correct positions of edges. The other is that it makes region competition more immune to the noises.

In order to alleviate the third problem, i.e., the weak edge problem, a weak edge enhancement scheme is proposed in this paper. To prevent a region from flooding out of the desired area, each weak edge located on the slowly varying slope is enhanced according to their position on the slope and the length of the slope. The idea is to amplify the edge information for the edges on the long, slow varying slopes and on the desired positions of the slopes, such that these edges may exert strong enough force to catch the boundary of a region.

This paper is organized as follows. The early vision model to be used in the discrete region competition is first described in Section II. The proposed discrete region competition is presented in Section III. The weak edge enhancement technique is proposed in Section IV. Experimental results and discussions are provided in Section V and Conclusions are given in Section VI.

II. THE EARLY VISION MODEL

At least three types of edges may be found in an ultrasound image. One is the edge formed by two regions of different gray levels. Another is the edge in between two different textures. And, the other is the hybrid of the first two. Detection of the first type of edges has been studied extensively and elegant edge detection algorithms can be found elsewhere [6]. On the other hand, texture image segmentation is still far from practical, especially for the natural images, though it has also been studied with great efforts. Nevertheless, texture image segmentation based on early vision models has received a wide attention because of the great capability of human visual process. Many researches on texture image segmentation [7-13] based on early vision models have been carried out in the past. The general idea of early vision model approaches is to perform segmentation on the neuroimages, i.e., an intermediate representation obtained by convolving the ultrasound image with the point spread functions (PSFs) of the neurons in the V1 area of the brain such as a bank of Gabor functions.

Since the texture structure of an ultrasound image is much more complex than that considered in most previous works and none of the algorithms in these works were designed for ultrasound images, we have proposed a new early vision model [3-4] recently for ultrasound image segmentation. Unlike the previous vision models in which the Gabor functions (or some other functions closely simulating the receptive fields of V1 cells) were applied to the entire image, in our model, the image is decomposed into overlapped blocks of subimages. Each subimage is convolved with N Gabor functions with different central frequencies and bandwidths. By half-wave rectifying each convolved subimage which generates one positive subimage and one negative subimage, two values can be obtained by summing up all pixel values in the positive and negative subimages, respectively. As a result, each block of subimage can be associated with a feature vector with $2N$ elements computed from N convolved subimages. Then, the *distance map* for the image may be attained by assigning the length of the feature vector for each block to the center pixel of the block. A more detailed description for this early vision model may be found in [4-5].

The distance map highlights not only the edge of two different textures, but also that of two regions with different gray levels. For instance, the distance map of the ultrasound image in Fig. 1 is shown in Fig. 2. It is observed that the edges are highlighted with high intensities in Fig. 2. However, it should be noted that some desired edges are invisible after the distance map was quantized into 256 gray scales. Those parts are considered as weak edges, which require further amplification to form barriers for region competition.

Figure 1. An ultrasound image with the object of interest in the middle

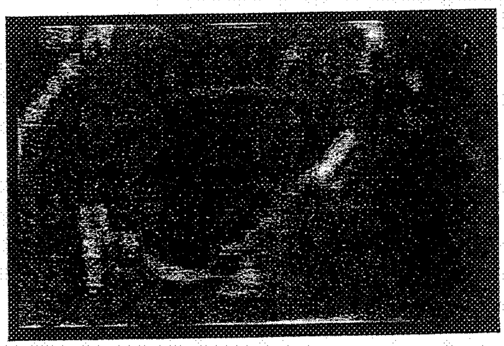

Figure 2. The distance map of the image in Fig. 1.

III. DISCRETE REGION COMPETITION

Region competition was originally proposed by Zhu and Yuille [1]. It unifies the perspectives of the snake and balloon model [14-15], region growing, region splitting, region merging, energy models, Bayes models, and the minimum description length principle. The global energy function employed in their algorithm is based on the log-likelihoods and a penalty term of arc length. The movement of boundary pixels is controlled by the steepest descent direction of the global energy function, which is equivalent to the competition by likelihood ratio tests. Although region competition has demonstrated a great feasibility for many types of images, it can easily fail on an ultrasound image due to the tissue-related textures, speckle noises and weak edges.

By combining the advantages of the early vision model, the discrete concept, the statistical modeling of speckle noises and the region competition, the discrete region competition approach is proposed to alleviate the dilemma caused by the textures and the speckle noises. Besides, a weak edge enhancement technique, which will be presented in the next section, is also incorporated into the discrete region competition algorithm to ease the weak edge problem. The proposed discrete region competition approach is composed of five major parts as described in the following.

Parameter estimation by the maximum likelihood estimate (MLE)

As in the Zhu and Yuille's region competition algorithm, the whole image R, including the background, is partitioned into M disjoint regions, i.e., $R = \bigcup R_i, R_i \bigcap R_j = \emptyset, i = 1,2,\ldots,M$. The energy function considered here is [1]

$$E(\Gamma,\{\sigma_i\}) = \sum_{i=1}^{M}\left\{\frac{u}{2}\oint_{\partial R_i} ds - \log P(R_i|\sigma_i)\right\}, \tag{1}$$

where $\Gamma_i = \partial R_i$ is the boundary of R_i, $\Gamma = \bigcup \Gamma_i$ is the total boundaries, $\log P(R_i|\sigma_i)$ is the log-likelihood of the pixels in region R_i and $u > 0$ is a weighting factor. The weighting factor is set to equalize the scales of the log-likelihood and the arc length terms in this study.

From Eq. (1), it is obvious that selecting an appropriate parameter to correctly describe the characteristics of each region is an important step for the proposed algorithm. Since the speckle is the major feature in ultrasound images, it is reasonable to choose the statistical parameter that may closely represent the distribution of the speckles. According to the definition of speckle in the book of Goodman [16] on statistical optics:

> "When images are formed by use of highly coherent light produced by a laser on an object composed of surfaces that are rough on the scale of an optical wavelength, they are found to have a granular appearance. These chaotic and unordered patterns have come to be known as *speckle*."

The noises on the ultrasound images are of the same phenomena. Since the speckle noises come from scatters smaller than the sample volume and one sample volume contains many scatterers, the signal received by a transducer is a superimposition of all scatterings received. Every reflected signal from a scatter has a different amplitude and phase angle. It is modeled as a random walk in the complex plane constituted by the axes of amplitude and phase angle. By the central limit theorem, the joint distribution of the amplitude and phase angle of the sum of scattering waves can be approximated by a Gaussian Distribution in the complex plane when the number of scatters is large. Thus, the resulting amplitude of the superimposed scatterings can be modeled by a Rayleigh distribution. The detail discussion can be found in Burckhardt [2] or Goodman [16].

Assume there are n_i pixels inside one region R_i, and the gray level of every pixel I_j in this region, is independently and identically distributed as a Rayleigh distribution with a parameter $\sigma_i > 0$. The probability density function of I_j is

$$P(I_j|\sigma_i) = \frac{I_j}{\sigma_i^2} e^{\frac{-I_j^2}{2\sigma_i^2}}. \tag{2}$$

The likelihood of this region is

$$L(\sigma_i|R_i) = P(R_i|\sigma_i) = \prod_{j=1}^{n_i} P(I_j|\sigma_i) = \prod_{j=1}^{n_i} \frac{I_j}{\sigma_i^2} e^{\frac{-I_j^2}{2\sigma_i^2}}. \tag{3}$$

The maximum likelihood estimate (MLE) of σ_i of this region becomes

$$\hat{\sigma}_i = \sqrt{\frac{\sum_{j=1}^{n_i} I_j^2}{2n_i}}. \tag{4}$$

If the gray level of an ultrasound image is obtained after a logarithmic compression transformation of the reflected wave [17-18], the model of the log-compressed gray level X_j in the R_i becomes

$$X_j = D \ln I_j + G, \quad j = 1,2,\ldots,n_i, \tag{5}$$

where I_j is the input to the compression block, X_j is the output of the compression block, D is a parameter of the compressor which represents the dynamic range of input, and G is the linear gain of the compressor. The resulting distribution for X_j is

$$P(X_j) = \frac{1}{\lambda}\exp\{-g_i - \exp(-g_i)\}, \tag{6}$$

where $g_i = \frac{\rho - X_j}{\lambda}$, $\rho = D\frac{\ln(2\sigma^2)}{2} + G$, and $\lambda = \frac{D}{2}$.

The likelihood is the product of $P(X_j)$. By the invariance property of the MLE, the MLE for σ_i in the transformed model is the same as that in Eq. (4) with the replacement of I_j by $e^{\frac{X_j - G}{D}}$ when D and G are known. When D and G are unknown, the MLE for (σ_i, D, G) are obtained by solving the corresponding three score equations. For simplicity, the Rayleigh distribution is used in our simulation and empirical studies. Therefore, the MLE of the parameter σ_i of the Rayleigh distribution would be $\hat{\sigma}_i$ as given Eq. (4) for the ith region R_i.

Movement along the steepest descent direction

After $\hat{\sigma}_i$ is estimated, the direction of movement is searched along the steepest descent direction. The motion equation of each point $\vec{v} = (x, y)$ on the boundary ∂R is found by the variational technique of the continuous energy function,

$$\frac{d\vec{v}}{dt} = -\frac{\delta E(\Gamma, \{\sigma_k\})}{\delta\vec{v}} = \sum_{k \in Q_{(\vec{v})}} \left\{ -\frac{u}{2}\kappa_{k(\vec{v})} + \log P\left(I_{(v)} \middle| \sigma_k\right) \right\} \vec{n}_{k(\vec{v})}, \quad (7)$$

where $Q_{(\vec{v})} = \{k | \vec{v} \in \Gamma_k$ is the collection of regions that share the boundary point $\vec{v}$, $\kappa_{k(\vec{v})} = \frac{\dot{x}\ddot{y} - \ddot{x}\dot{y}}{\left(\dot{x}^2 + \dot{y}^2\right)^{\frac{3}{2}}}$ is the curvature of Γ_k at $\vec{v}$, $\vec{n}_k = \frac{1}{\sqrt{\dot{x}^2 + \dot{y}^2}} \begin{pmatrix} \dot{y} \\ -\dot{x} \end{pmatrix}$ is the unit normal vector at $\vec{v}$, and $\log P\left(I_{(\vec{v})} \middle| \sigma_k\right)$ is the log-likelihood of the intensity at $\vec{v}$ in region k. The discrete approximation of the steepest descent direction in Eq. (7) is used as the movement direction.

Growing or competition by the likelihood ratio tests

If $\vec{v}$ is in the boundary of a region and the background, then Eq. (7) becomes

$$\frac{d\vec{v}}{dt} = \left(-\frac{u}{2}\kappa_{(\vec{v})} + \left(\log P\left(I_{(\vec{v})} \middle| \sigma_i\right) - \log P_0\right) \right) \vec{n}_{(\vec{v})}. \quad (8)$$

Here, the background is modeled as a uniform distribution and P_0 is the uniform probability density function over the range of intensities, e.g., [0,255]. It is actually a likelihood ratio test. If the intensity $I_{(\vec{v})}$ has a higher probability in region i than that in the background, the point $\vec{v}$ expands and the region grows at that point. Otherwise, the region shrinks at that point. That is, the region competes with the background.

If $\vec{v}$ is on the common boundary of regions R_i and R_j, then $\vec{n}_i = -\vec{n}_j$, and $\kappa_i\vec{n}_i = \kappa_j\vec{n}_j$. The motion equation for $\vec{v}$ becomes

$$\frac{d\vec{v}}{dt} = \left(-u\kappa_{i(\vec{v})} + \left(\log P\left(I_{(\vec{v})} \middle| \hat{\sigma}_i\right) - \log P\left(I_{(\vec{v})} \middle| \hat{\sigma}_j\right)\right) \right) \vec{n}_{i(\vec{v})} \quad (9)$$

For the Rayleigh distribution, it is

$$\frac{d\vec{v}}{dt} = \left(-u\kappa_{i(\vec{v})} + \left(2\log\left(\frac{\hat{\sigma}_j}{\hat{\sigma}_i}\right) - I_{(\vec{v})}\left(\frac{1}{2\hat{\sigma}_i^2} - \frac{1}{2\hat{\sigma}_j^2}\right) \right) \right) \vec{n}_{i(\vec{v})} \quad (10)$$

The second term in Eq. (9) is exactly a likelihood ratio test. If the intensity $I_{(\vec{v})}$ more likely belongs to region i according to the likelihood ratio test, then $\vec{v}$ moves along $\vec{n}_i$, and the region i grows at that point. Otherwise, the region j grows at that point. That is, the regions compete with each other when they meet together. Similarly, when three or more regions share the same boundary point, the competition decides the movement of that boundary point.

Capture of texture boundary by the early vision model

Basically, the first three parts mentioned above follows the spirit of Zhu and Yuille's region competition algorithm, except that the MLE of the parameter σ_i of the Rayleigh distribution rather than the normal distribution is employed, which may account for speckle noises more accurately. Since region growing (the major mechanism in region competition) is primarily based on the information offered by each single region, it is easily trapped by the false edges given by the noises or the micro patterns of textures. Therefore, it is reasonable to expect that region competition can easily fail on ultrasound images due to the intrinsic speckle noises and textures. One possible way to improve the region competition algorithm is to add a gradient term to the energy function, as suggested in [1]. It is because when a pixel moves to a new position that is on an edge of an object, the magnitude of the gradient will increase. That is, with a gradient term in the energy function, the edges may be easier to catch in the process of region growing and competition in theory. However, since ultrasound images are usually filled with speckles and tissue-related textures, adding a conventional gradient term may not be so useful as expected in practice. The reasons are

- the gradients computed from the false edges of speckle noises and the micro patterns of textures may be comparable to or larger than the gradients of the desired edges,
- if the image is blurred attempting to eliminate the speckles and textures, the derived edges may be shifted from the correct position, or the desired edges may be lost.

Instead of using the conventional gradients, in this paper, we propose to use the distance map to guide the boundary of each region toward the desired edges. The distance map is anticipated to outperform the conventional gradients since the distance map is derived based on an early vision model, which has the potential to identify boundaries for different textures as well for regions with different gray levels. Practically, the desired edges will be located at the peak points of a distance map. Just like the conventional gradients, one may consider to use the magnitude of a distance map as a term in the energy function. However, this approach does not guarantee that the boundary of a region will coincide with the desired edges since the final boundary of a region is determined by all energy terms, not only by the magnitude of a distance map. In order to ensure the boundary of a region to agree with the desired edges, the discrete concept is introduced into the region competition algorithm as follows.

Moving along the steepest descent direction discretely

Rather than adding the magnitude of a distance map into the energy function, the discrete concept suggests to move each point of a region boundary only over the peaks of the distance map along the steepest descent direction. That is, the movement is discrete in contrast to the continuous movement with which all points along the steepest descent direction will be considered. The advantages of the discrete concept are in two folds. One is that the final boundary of a region is expected to have a much better coincidence with the desired edges compared with that obtained by the continuous movement or by adding the magnitude of a distance map to the energy function. It is because once region competition comes to a steady state, every boundary point must be on the correct position of an edge. The other is that it has a better chance to escape from the local minima on the false edges given by the speckles and the micro patterns of textures. The reason is the searching space for the minimal energy state is much smaller and concise compared to that employed by the conventional approaches.

IV. WEAK EDGE ENHANCEMENT

The discrete region competition proposed in this paper is expected to be more immune to the noises and the false edges caused by the speckles and textures. Also it is more likely for the boundary of each region to be coincident with the desired edges. However, when the desired edges are weak, for instance, the edges on slowly-varying slopes, the discrete region competition approach may fail to catch these edges and the moving points stretch out from weak edges easily. To solve this problem, in this study, we propose a weighting parameter for weak edge enhancement, which is to be incorporated in the discrete region competition algorithm. By multiplying the weighting parameter, k, to the likelihood function of background, the log-likelihood of the background increases and the boundary point is more inclined to stay at the same position or shrink back. Thus the growing force at weak edges is reduced and the boundary is able to stop on weak edges.

The weighting parameter, k, is a function of the position of the weak edge point on the slope and the length of the slope. Suppose that the desired edge position is on the top of a slope. Then, along the direction of $\vec{n}_{(\vec{v})}$ or $-\vec{n}_{(\vec{v})}$, two numbers, l_1 and l_2, are obtained by counting the number of the pixels from $\vec{v}$ along the non-decreasing and non-increasing intensity directions, respectively. The maximum searching range in each direction is r pixels. Since $1 \le l_1 + 1 \le r+1$ and $1 \le l_2 + 1 \le r+1$,

$$\frac{1}{r+1} \le \frac{l_1 + l_2 + 2}{2(r+1)} \le 1$$

and

$$\frac{1}{2(l_1 + l_2 + 1)} \le \frac{l_1 + 1}{2(l_1 + l_2 + 1)} \le \frac{1}{2}.$$

The longer the slope is, the larger $\frac{l_1 + l_2 + 2}{2(r+1)}$ is. The smaller l_1 is or the larger l_2 is, the closer the point is to the top of the slope, and the larger $\cos\left(\frac{(l_1+1)\pi}{2(l_1+l_2+1)}\right)$ is. When the boundary is aimed to stop around the top in a long slope, the following weighting parameter is proposed:

$$k = \left[\frac{(l_1 + l_2 + 2)}{2(r+1)} \cos\left(\frac{(l_1 + 2)\pi}{(l_1 + l_2 + 1)}\right) + 1\right]^c \tag{11}$$

for a power parameter c. Thus, $1 < k < 2^c$, and the edge at each $\vec{v}$ is enhanced adaptively according to its position and the length of the slope that it is on. The power c is determined empirically in this study.

The weighting parameter is incorporated into the discrete region competition algorithm to provide a barrier force to hinder a region from expanding across over the desired weak edges. As an example, consider the case that a region competes with the background. Assume the distribution of background is uniformly distributed over [0,255]. The movement in Eq. (8) for a point $\vec{v}$ in a region is modified to be the sum of the following two terms,

$$\frac{d\vec{v}}{dt} = (c_1 + c_2)\vec{n}_{(\vec{v})} \tag{12}$$

where

$$c_1 = -\frac{u}{2}\kappa,$$

$$c_2 = \log P\left(I_{(\vec{v})} \middle| \hat{\sigma}_i\right) - \log\left(\frac{k}{255}\right).$$

If $c_1 + c_2 > 0$, $\vec{v}$ moves toward the direction of normal vector $\vec{n}$ and inflates the region. Otherwise, $\vec{v}$ shrinks the region along the opposite direction of $\vec{n}$. When a desired weak is encountered, since k becomes relatively larger, it makes c_2 smaller and hence reduces the inflation force.

V. EXPERIMENTAL RESULTS AND DISCUSSIONS

The proposed discrete region competition approach and the weak edge enhancement technique have been applied to the clinical ultrasound images. As an example, Figs. 3 and 4 illustrates the segmentation results using the conventional region growing algorithm with different threshold levels for the ultrasound image shown in Fig. 1. If the threshold level is high, the region stretches out through the weak edges as seen on the both side of the region of interest (ROI). If the threshold level is low, then the segmented region shrinks with a lot of holes inside.

Figure 3. Region growing by intensity levels with a high threshold.

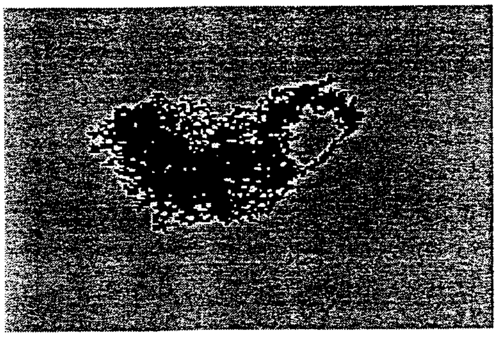

Figure 4. Region growing by intensity levels with a low threshold.

Figure 5. The segmentation result obtained by using the region competition in two-region mode, assuming Rayleigh Distribution

To see the effect of the early vision model, discrete concept and the weak edge enhancement, various experiments have been carried out on the same ultrasound image given in Fig. 1. The goal is to segment out the triangle-like region in the central area of Fig.1. Suppose Zhu and Yuille's region competition is employed. One way to obtain this region is to use the one-region mode, i.e., only one region grows and competes with the background. However, this way may get a result similar to Fig. 3. In other word, the only region may flood out the desired region though the weak edges at the left and right sides of the triangle. In order to block the growing of the region at the weak edges, two-region mode needs to be employed and the initial seed of the left region should be placed close to the left weak edge. Fig. 5 gives the segmentation result using two-region mode by the region competition. Rayleigh distribution is assumed in this experiment. It is clear that the boundaries of segmented regions are not close to the desired boundaries.

If the discrete concept is combined with the region competition in such a way that only the peaks in the original image (Fig. 1) are considered in the searching process for next pixel position to move, the segmentation result is given in Fig. 6. Note that two-region mode is still required to hinder the right region from stretching out of the left weak edge. Comparing Figs. 5 and 6, one may find that the boundary of the right region in Fig. 6 has a better coincidence with the texture boundaries for strong edges than that in Fig. 5 dose. However, the right region in Fig. 6 floods out of the right weak edge due to the local peaks caused by the noises.

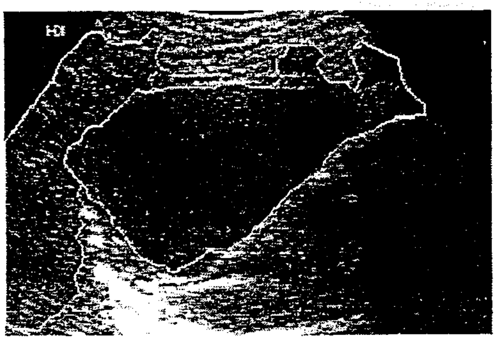

Figure 6. The segmentation result obtained by combing region competition and discrete concept in two-region mode.

When the discrete region competition is employed, i.e., it includes region competition with Rayleigh distribution assumed, discrete concept and early vision model, the segmentation result is demonstrated in Fig. 7. The edges are highlighted in the peak points of the distance map as shown in Fig. 2. Moreover, the noises have been drastically suppressed. Note that two-region mode is also required to prevent the right region from growing out of the weak edges. Like in Fig. 6, the boundary of the right region derived by the discrete region competition coincides with the texture boundary better than that derived by the region competition. But unlike in Fig. 6, this experiment successfully catches the right weak edge.

When the weak edge enhancement is incorporated into the discrete region competition, the segmentation result is presented in Fig. 8. Plausibly, reasonable boundaries have been found simply with one-region mode. These encouraging results have shown that the proposed discrete region competition and weak edge enhancement techniques are very effective for ultrasound image segmentation. And combining the discrete concept and the distance map may dramatically increase the accuracy in locating the desired edges.

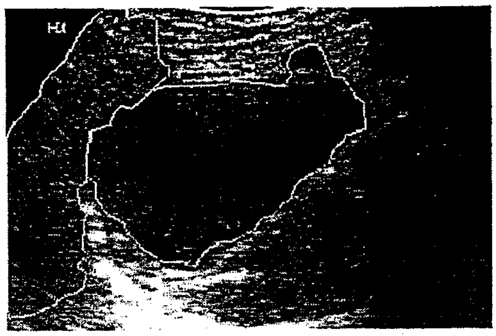

Figure 7. The segmentation result obtained by using the discrete region competition, including the early vision model and the discrete concept, in two-region mode.

Figure 8. The segmentation result obtained by using the discrete region competition incorporating weak edge enhancement in one-region mode

VI. CONCLUSIONS

Ultrasound image segmentation is a nontrivial task due to the intrinsic speckle noises and the tissue-related textures. In this paper, we present a novel segmentation algorithm for ultrasound images, namely, discrete region competition. The discrete region competition has four distinguished features. First of all, it takes advantage of region competition originally proposed by Zhu and Yuille [1] as the basic mechanism for region deformation. Secondly, it takes into account the statistical model of speckle noises in the algorithm. Thirdly, it adopts the distance map derived from our early vision mode to catch both the texture boundary as well as the boundary of two regions with different gray levels. Lastly, it combines the discrete concept to ensure the boundary of each region to be coincident with the desired edges. In addition, to catch the weak edges which are usually missed by conventional approaches, a new weak edge enhancement technique has also been proposed in this paper. By incorporating weak edge enhancement into the discrete region competition, the implementation results have shown a great success for ultrasound image segmentation.

REFERENCES

[1] S. C. Zhu, and A. Yuille, "Region Competition: Unifying Snakes, Region Growing, and Bayes/MDL for Multiband Image Segmentation," *IEEE Trans. PAMI.*, vol. 18, no. 9, pp. 884-900, 1996.

[2] C. B. Burckhardt, "Speckle in Ultrasound B-Mode Scans," *IEEE Trans. Ultrasonics*, vol. SU-25, pp. 1-6, 1978.

[3] C. M. Chen and C. B. Lin. Sept. 1997: "Ultrasound Image Segmentation Based on an Early Vision Model," *World Congress on Medical Physics and Biomedical Engineering*, Nice, France.

[4] C. B. Lin, C. M. Chen and S. Su. Oct. 1997: "A Computational Early Vision Model for Segmentation of Clinical Ultrasound Images," 19th Annual International Conference of the IEEE EMBS, Chicago, Illinois, U.S.A.

[5] C. M. Chen, H. H. S. Lu and Y. C. Lin. Feb. 1998: "A New Ultrasound Image Segmentation Algorithm Based on an Early Vision Model and Discrete Snake Model," SPIE International Symposium on Medical Imaging 1998, San Diego, California, U.S.A.

[6] J. C. Russ, "The image processing handbook," Boca Raton, Fla.: CRC Press, 1992.

[7] T. N. Tan, "Texture edge detection by modelling visual cortical channels," *Pattern Recognition* vol. 28, no. 9, pp. 1283-1298, 1995.

[8] J. Malik and P. Perona, "Preattentive texture discrimination with early vision mechanisms," *J. Opt. Soc. Am.* vol. A7, pp. 923-932, 1990.

[9] A. K. Jain and F. Farrokhnia, "Unsupervised texture segmentation using Gabor filters," *Pattern Recognition*, vol. 24, no. 12, pp. 1167-1186, 1991.

[10] M. M. Van Hulle and T. Tollenaere, "A modular artificial neural network for texture processing," *Neural Networks*, vol. 6, pp. 7-32, 1993.

[11] A. C. Bovik, M. Clark, and W.S. Geisler, "Multichannel texture analysis using localized spatial filters," *IEEE Trans. PAMI*, vol. 12, no. 1, pp. 55-73, 1990.

[12] D. Dunn, W. E. Higgins, and J. Wakeley, "Texture segmentation using 2-D Gabor elementary functions," *IEEE Trans. PAMI*, vol. 16, no. 2, pp. 130-149, 1994.

[13] K. P. Hui, Y. S. Cheung, C. H. Leung, "Computer texture boundary detection based on human visual perception model," *1994 Int'l Symp. on Speech, Image Processing, and Neural Networks.*

[14] M. Kass, A. Witkin and D. Terzoulos, "Snake:Active contour models," *Int. J. Comput. Vision*, vol. 1, pp. 321-331, 1987.

[15] L. D. Cohen, "On active contour models and balloons," Comput *Vision, Graphics, and Image Processing: Image Understanding*. vol. 53, no. 2, pp. 211-218, 1991.

[16] J. W. Goodman, *Statistical Optics*, Wiley, New York, p.347, 1985.

[17] D. Kaplan and Q. Ma, "On The Statistical Characteristics of Log-compressed Rayleigh Signals: Theoretical Formulation and Experimental Results,"*J. Acoust. Soc. Am.*, vol. 95, no. 3, pp. 1396-1400, 1994.

[18] V. Dutt and J. F. Greenleaf, "Adaptive speckle reduction filter for log-compressed B-scan images," *IEEE Trans. Med. Imaging*, vol. 15, no. 6, pp. 802-813, 1996.