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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 inherently difficult to analyze due to their echo texture, speckle noise and weak edges. Taking into account these characteristics, we present a new region-based approach for ultrasound image segmentation. It is composed of two primary algorithms, discrete region competition and weak edge enhancement. The discrete region competition features four techniques, region competition, statistical modeling of speckle, early vision modeling, and discrete concepts. In addition, to prevent regions from leaking out of the desired area across weak edges, edges located on the slowly varying slope are enhanced according to their position on the slope and the length of the slope. This new approach has been implemented and verified on clinical ultrasound images.

Keywords: Ultrasound image segmentation; Speckle; Early vision; Region segmentation

1. Introduction

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

Even though region-based approaches have been well studied and successfully applied to those images of good image quality, classical techniques can easily fail in segmentation of ultrasound images due to three inherent problems in these images. The first problem is the "echo texture", which results from different transmission speeds in different media. Secondly, coherent interference of backscattered echoes produce speckle noise. The third one is the weak edge on the desired boundary, which is caused by artifacts or by similar acoustic properties of adjacent tissues. While problems of texture and speckle noise may form false edges, weak edges may lead to missing edges along the desired boundary.

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To cope with the first two problems, we propose a new region-based approach, termed "discrete region competition", for ultrasound image segmentation. Region competition was originally proposed by Zhu and Yuille (1996), 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 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 regions meet, pixels at the boundary move according to the comparisons of log-likelihoods with the parameters estimated by the maximum log-likelihood approaches, that is, according to likelihood ratio tests.

Region competition has been shown to be effective in many image segmentation problems. Zhu et al. (1998) discussed the possible extension of this technique to color and texture segmentation with the modeling of texture. In order to conquer the interference of the tissue-related texture and the speckle noise in ultrasound images, we propose a discrete region competition approach combining the advantages of region competition with the statistical modeling of speckle, early vision model, and the *discrete* concept for ultrasound image segmentation. The statistical modeling is to account more accurately for the statistical properties of speckle noise in ultrasound images. To do so, we employ the Rayleigh distribution or its transformation (Burckhardt, 1978) rather than the Gaussian distribution.

Early vision model generates information on edges between different texture in an ultrasound image (Chen and Lin, 1997; Lin et al., 1997; Chen et al., 1999; Chen et al., 2001). By mimicking human visual perception, we have shown that this model highlights edge information while suppressing speckle. The advantage of using the early vision model over the conventional edge detectors is that it can not only identify the edges between two uniform regions with different gray levels but also those between two regions with different texture.

The discrete concept was first proposed for the snake model (Chen et al., 1999) to overcome the local minima resulting from texture, speckle and artifacts. The idea is to move the boundary points of each region over the peaks on the distance map generated by the early vision model. The rationale is two-fold. 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 noise.

In order to alleviate the third problem of weak edges, an enhancement scheme is proposed. To prevent a region from leaking 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 of the desired position on the slow varying slopes such that these edges may exert a 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 2. The proposed discrete region competition is presented in Section 3. The weak edge enhancement technique is proposed in Section 4. Empirical results and discussions are provided in Section 5. Conclusions are given in Section 6.

2. 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 between two different texture. The other is the hybrid of the first two types. Detection of the first type of edges has been studied extensively (Russ, 1992). On the other hand, texture image segmentation is still far from practical, especially for empirical images, though it has also been studied with great effort. Recently, texture image segmentation based on early vision models has received wide attention because of the growing understanding of human visual perception and current computing power. Much research on texture image segmentation based on early vision models have been carried out in literature (Tan, 1995; Malik and Perona, 1990; Jain and Farrokhnia, 1991; Van Hulle and Tollenaere, 1993; Bovik et al., 1990; Dunn et al., 1994; Hui et al., 1994; Zhu and Yuille, 1996; Zhu et al., 1998). The general idea of early vision model approaches is to perform segmentation on the neuroimages, the intermediate representation obtained by convolving the image with the point spread functions (PSFs) that mimic the neurons in the V1 cells of the brain. The typical PSFs used are 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 algorithm in these works was designed for ultrasound images, we have recently proposed a new early vision model (Chen and Lin, 1997; Lin et al., 1997; Chen et al., 1999; Chen et al., 2001) for ultrasound image segmentation. Previous vision models mostly apply the Gabor functions (or some other functions closely simulating the receptive fields of V1 cells) to the entire image. In our model, the whole 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 computed from N convolved subimages. Then the distance map for the image is attained by assigning the length of the feature vector for each block. A more detailed description and numerical comparisons of edge detection in ultrasound images for this early vision model can be found in other papers (Lin et al., 1997; Chen et al., 1999; Chen et al., 2001).

The distance map highlights not only the edge of two different texture, 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 is also noted that some desired edges are invisible. Those parts are considered as weak edges, which require further amplification to form barriers for region competition.

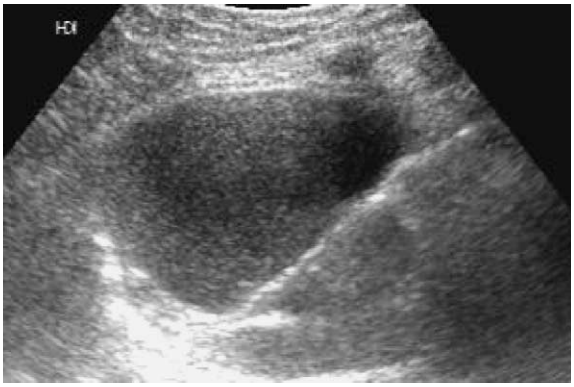

Fig. 1. An ultrasound image with the object of interest in the middle.

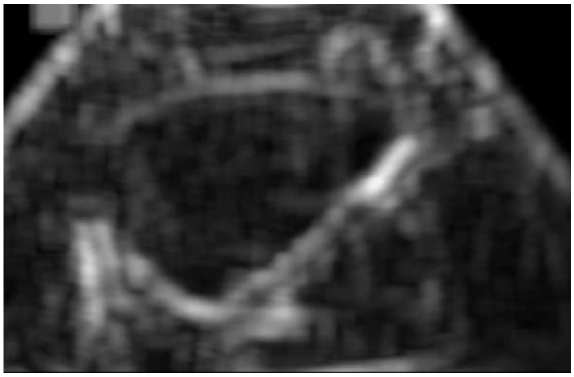

Fig. 2. The distance map of the image in Fig. 1.

3. Discrete region competition

Region competition was originally proposed by Zhu and Yuille (1996). It unifies the perspectives of the snake and balloon model (Kass et al., 1987; Cohen, 1991), 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 performing comparisons by likelihood ratio tests.

By combining the advantages of the early vision model, the discrete concept, the statistical modeling of speckle noise and the region competition, the discrete region competition approach is proposed to alleviate the difficulties of segmentation caused by the texture and the speckle noise. Besides, a weak edge enhancement technique, which will be presented in the next section, is also incorporated into the discrete region competition algorithm to resolve the problems of weak edges. The proposed discrete region competition approach is composed of five major parts as described in the followings.

3.1. Parameter estimation by the maximum likelihood estimate

Suppose that the whole image R, including the background, is partitioned into M disjoint regions, $R = \cup R_i$, $R_i \cap R_j = \emptyset$, $i = 1, 2, 3, \ldots, M$. Similar to Eq. (7) in Zhu and Yuille (1996), the energy function is considered to be

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

where $\Gamma_i = \partial R_i$ is the boundary of R_i, $\Gamma = \cup \Gamma_i$ is the total boundaries, $\log P(R_i|\sigma_i)$ is the log-likelihood of the pixel intensities in region R_i with parameter σ_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 probability model 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 probability model that can represent the distribution of the speckle.

The following definition of speckle in quoted from the book of Goodman (1985, p. 347) 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 noise on the ultrasound images are of the same phenomena. Since the speckle noise 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 (1978) or Goodman (1985).

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

$$P(I_j|\sigma_i) = \frac{I_j}{\sigma_i^2} \exp\left(\frac{-I_j^2}{2\sigma_i^2}\right). \qquad (2)$$

The likelihood of this region is

$$P(R_i|\sigma_i) = \prod_{j=1}^{n_i} P(I_j|\sigma_i) = \prod_{j=1}^{n_i} \frac{I_j}{\sigma_i^2} \exp\left(\frac{-I_j^2}{2\sigma_i^2}\right). \qquad (3)$$

The maximum likelihood estimate (MLE) of σ_i of this region turns out to be

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

If the gray level of an ultrasound image is obtained after a logarithmic compression transformation of the reflected wave (Kotropoulos and Pitas, 1992; Kaplan and Ma, 1994; Dutt and Greenleaf, 1996), the model of the log-compressed gray level X_j in the region 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. Through the transformation of random variables (Dutt and Greenleaf, 1996, p. 804–805), the resulting distribution for X_j is

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

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

3.2. Movement along the steepest descent direction

After σ_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,

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

where $Q_{(\vec{v})} = \{k | \vec{v} \in \Gamma_k\}$ is the collection of regions that share the boundary point $\vec{v}$, $\kappa_{k(\vec{v})} = (\dot{x}\ddot{y} - \ddot{x}\dot{y})/(\dot{x}^2 + \dot{y}^2)^{3/2}$ is the curvature of Γ_k at $\vec{v}$, $\vec{n}_k = 1/\sqrt{\dot{y}^2 + \dot{x}^2}\begin{pmatrix} \dot{y} \\ -\dot{x} \end{pmatrix}$ is the unit normal vector at $\vec{v}$, and $\log P(I_{(\vec{v})}|\sigma_k)$ 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.

3.3. Growing or movement by the likelihood ratio tests

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

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

Here, the background is modeled as a uniform distribution and P_0 is the uniform probability density function over the range of intensities, like $[0, 255]$. This 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 region between 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

$$\begin{aligned}\frac{d\vec{v}}{dt} = -u\kappa_{i(\vec{v})}\vec{n}_{i(\vec{v})} &+ (\log P(I_{(\vec{v})}|\hat{\sigma}_i) \\ &- \log P(I_{(\vec{v})}|\hat{\sigma}_j))\vec{n}_{i(\vec{v})}.\end{aligned} \tag{9}$$

For the Rayleigh distribution, it is

$$\begin{aligned}\frac{d\vec{v}}{dt} &= -u\kappa_{i(\vec{v})}\vec{n}_{i(\vec{v})} \\ &+ \left[2\log\left(\frac{\hat{\sigma}_j}{\hat{\sigma}_i}\right) - I_{(\vec{v})} - \left(\frac{1}{2\hat{\sigma}_i^2} - \frac{1}{2\hat{\sigma}_j^2}\right)\right]\vec{n}_{i(\vec{v})}.\end{aligned} \tag{10}$$

The second term in Eq. (9) is exactly a likelihood ratio test. If the intensity $I_{(\vec{v})}$ is more likely belonging 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.

3.4. Capture of texture boundary by the early vision model

Basically, the first three parts mentioned above follow 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 accounts for speckle noise 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 noise or the micro patterns of texture. Therefore, we propose to use the distance map by the early vision model to guide the boundary of each region toward the desired edges. Since the distance map is derived based on an early vision model, it has the potential to identify boundaries for different texture as well for regions with different gray levels. Practically, the desired edges will be located at the peak points of a distance map. One may add 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.

3.5. Moving along the steepest descent direction discretely

Rather than adding the magnitude of a distance map into the energy function, the discrete concept suggests that we 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 applying the discrete concept are two-fold. 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 speckle and the micro patterns of texture. The reason is the searching space for the minimal energy state is much smaller and more concise compared to that employed by the conventional approaches.

4. Weak edge enhancement

The discrete region competition proposed in this paper is expected to be more immune to the noise and the false edges caused by speckle and texture. 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 in the sense that the edges are on slowly varying slopes, the discrete region competition approach may fail to catch these edges and the moving points may easily stretch out from weak edges. To solve this problem, in this study we propose a weighting parameter for weak edge enhancement to be incorporated in the discrete region competition algorithm. By multiplying the weighting parameter, l, 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, l, is a function of the position of the boundary 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 nondecreasing intensity direction and nonincreasing intensity directions, respectively. The maximum searching range in each direction is set to be r pixels. Since $1 \leqslant l_1 + 1 \leqslant r + 1$, and $1 \leqslant l_2 + 1 \leqslant r + 1$, $1/(r + 1) \leqslant (l_1 + l_2 + 2)/2(r + 1) \leqslant 1$ and $1/2(l_1 + l_2 + 1) \leqslant (l_1 + 1)/2(l_1 + l_2 + 1) \leqslant 1/2$. The longer the slope is, the bigger $(l_1 + l_2 + 2)/2(r + 1)$ is. The smaller l_1 is or the larger l_2 is, the more the point is to the top of the slope, and the bigger $\cos(((l_1 + 1)\pi)/(2(l_1 + l_2 + 1)))$ is. As the boundary is aimed to stop around the top in a long slope, the following weighting parameter is proposed:

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

for a power parameter c. Thus, 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

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

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

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, l becomes relatively larger. This makes c_2 smaller and the inflation force is reduced thereof.

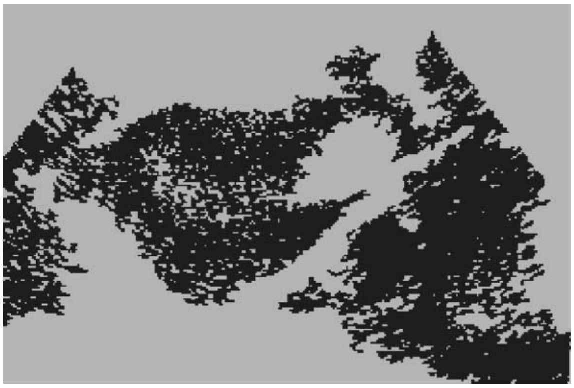

Fig. 3. Region growing by intensity levels with a high threshold.

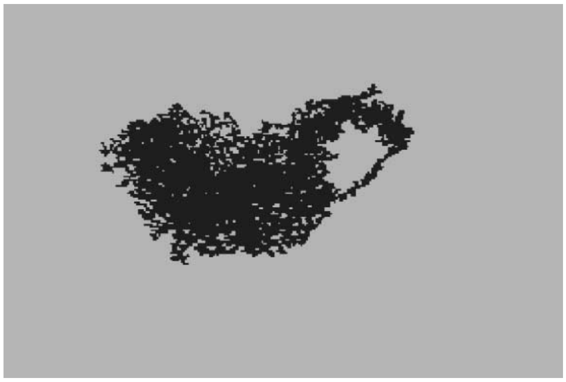

Fig. 4. Region growing by intensity levels with a low threshold.

5. Experimental results and discussions

The proposed discrete region competition approach and the weak edge enhancement technique are applied to clinical ultrasound images. As an example, Figs. 3 and 4 illustrate 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.

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 with only one region grows that competes with the background. However, this way may get a result similar to Fig. 3. In other words, the only region may leak out the desired region though the weak edges at the left and right sides of the ROI. 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, we obtain the segmentation result in Fig. 6. Note that two-region mode is still required to hinder the ROI 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. However, the right region in Fig. 6 leaks out of the right weak edge due to the local peaks caused by the noise.

When the discrete region competition is employed, i.e. it includes region competition with Rayleigh distribution, discrete concept and early vision model, we obtain the segmentation result in Fig. 7. The edges are highlighted in the peak points of the distance map as shown in Fig. 2. Moreover, the noise has 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

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

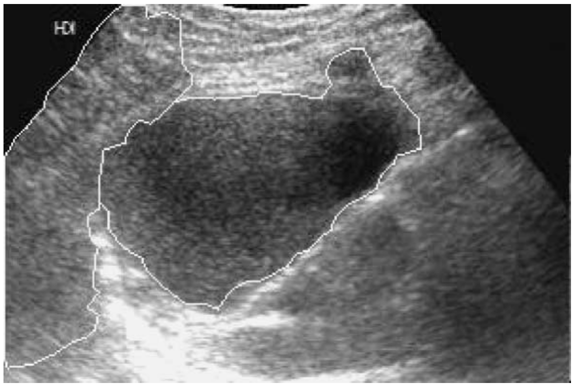

Fig. 7. The segmentation result obtained by using the discrete region competition, including the early vision model and the discrete concept, in two-region mode.

Fig. 5. The segmentation result obtained by using the region competition in two-region mode under the assumption of Rayleigh distribution.

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

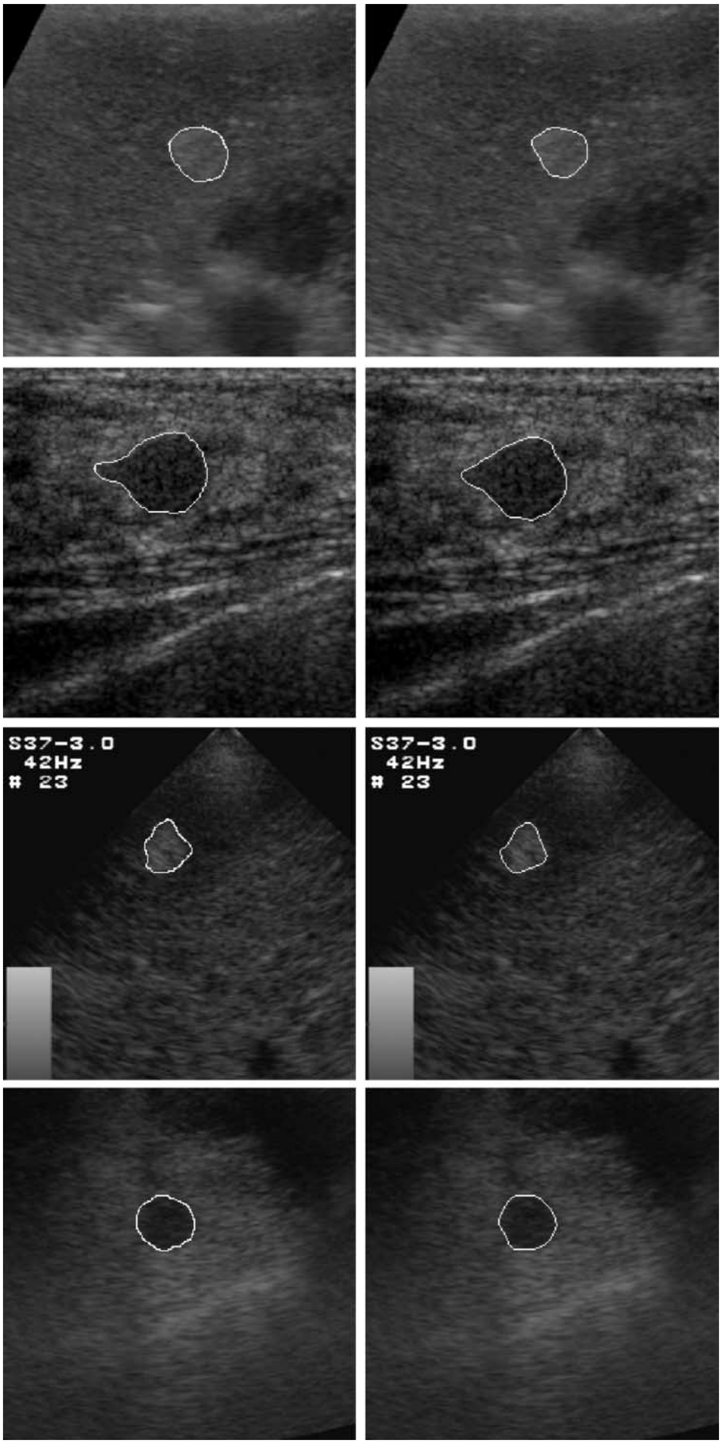

Fig. 9. The comparison studies of seven ultrasound images. The left column contains the ideal segmentation results by experts and the right column contains the segmentation results by using the discrete region competition incorporating weak edge enhancement in one-region mode.

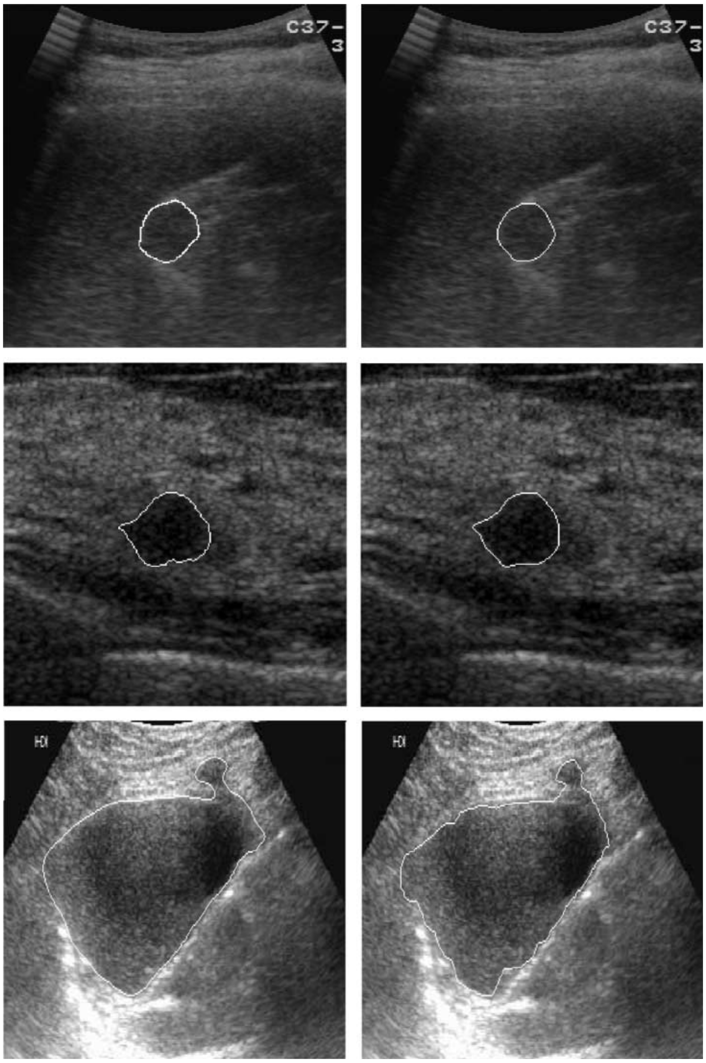

Fig. 9 (*continued*)

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 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.

Comparison studies for seven ultrasound images are performed and reported in Fig. 9. The left row contains the ideal segmentation by experts, while the right row contains the segmentation results by using the discrete region competition incorporating weak edge enhancement in one-region

Table 1
The mean and the standard deviation of the distances from the derived boundary in the test images at the right row of Fig. 9 to the desired boundary in those at the left row of Fig. 9 are reported in the unit of pixel

	Test image						
	1	2	3	4	5	6	7
Mean	1.5	2.9	2.0	0.7	1.1	2.2	2.8
Standard deviation	1.3	1.4	1.7	0.6	1.0	1.7	2.1

mode. The mean and the standard deviation of the distances from the derived boundary in the right row of Fig. 9 to the desired boundary in the left row of Fig. 9 are reported in Table 1 with the unit of pixel. The automatic segmentation results of the new method are close to the ideal segmentation.

6. Conclusions

Ultrasound image segmentation is a nontrivial task due to the intrinsic speckle noise and the tissue-related texture. In this paper, we present a novel segmentation algorithm for ultrasound images with discrete region competition and weak edge enhancement. The discrete region competition has four distinctive features. First of all, it takes advantage of region competition originally proposed by Zhu and Yuille (1996) as the basic mechanism for region deformation. Secondly, it models speckle noise statistically. Thirdly, it adopts the distance map derived from our early vision model to catch texture boundaries as well as the boundaries between regions with different gray levels. Lastly, it combines the discrete concept to ensure that the boundaries of each region coincide 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. Putting these all together, we have shown that our implementation successfully segments clinical ultrasound images.

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