International Journal of Medical, Medicine and Health Sciences
ISSN: 2517-9969
Vol:1, No:10, 2007

A Local Statistics Based Region Growing Segmentation Method for Ultrasound Medical Images

Ashish Thakur

Radhey Shyam Anand*

***Abstract*—** This paper presents the region based segmentation method for ultrasound images using local statistics. In this segmentation approach the homogeneous regions depends on the image granularity features, where the interested structures with dimensions comparable to the speckle size are to be extracted. This method uses a look up table comprising of the local statistics of every pixel, which are consisting of the homogeneity and similarity bounds according to the kernel size. The shape and size of the growing regions depend on this look up table entries. The algorithms are implemented by using connected seeded region growing procedure where each pixel is taken as seed point. The region merging after the region growing also suppresses the high frequency artifacts. The updated merged regions produce the output in formed of segmented image. This algorithm produces the results that are less sensitive to the pixel location and it also allows a segmentation of the accurate homogeneous regions.

***Keywords*—** local statistics, region growing, segmentation, and ultrasound images.

I. INTRODUCTION

THE advantages of ultrasound imaging, besides the absence of tissue damage, are low cost and minimal discomfort, but images are of a relatively poor quality and then analysis in general is complex due to data composition, described in terms of speckle formation. These speckles tend to mask the presence of low contrast lesion and reduce the ability of a radiologist to resolve the actual information. Due to speckle formation and attenuation artifacts, it is difficult to properly segment of the ultrasound image to detect interested objects with the correct position and shape. In addition, boundary edges are usually incomplete, missing or weak at some places [1].

There are a large number of different approaches on segmenting an images recently employed. For the ultrasound medical image segmentation, mostly the methods are focused on five main approaches, namely, thresholding technique [2], boundary-based method [3], region based methods [4], hybrid techniques which combine boundary and region criteria [5] and active contour based approach [6]. Thresholding techniques to use brightness constant called threshold value, and segment the pixels in the original image according to this threshold value. Such methods neglect all the spatial information of the image and do not manage well with noise or blurring at boundaries, which are generally encountered in the ultrasound images. The boundary-based methods use the pixel values changing rapidly at the boundary between two regions. In this procedure, 1) first the edge detector operators provide the edge pixels and 2) these edges are modifying to produce the close curves representing the boundaries between adjacent regions. But, to convert the edge pixels into the close boundary is very difficult task for the ultrasound image segmentation. The complement of the boundary-based method is known as region based segmentation. It is based on the principle that neighboring pixels within the one region have similar value [7]. Split-and-merge procedure is best known in the region-based category for the segmentation, but in all instances the speckles into ultrasound images upset the results. The hybrid techniques are based on the combination of boundary and region based segmentation i.e., morphological watershed processing. The watershed method is an example of the morphological image segmentation approach. This technique is guaranteed to produce closed boundaries even if the transitions between regions are of variable strength [8]. But, the watershed segmentation method encounters difficulty, if there is noise and indistinct boundaries in between the two adjacent regions. Another category for the image segmentation method is the active contour techniques, which is suitable for finding edges of a region whose gray scale intensities are significantly different from the surrounding region into the images [9].

In this paper, a local statistics based region merging scheme is proposed for segmentation of ultrasound medical image. This technique is broadly divided into four steps: 1) preparation of lookup table of local statistics of all pixels to be used for initial region growing procedure, 2) grouping of pixels satisfying a specify homogeneity criteria and produce the homogeneous region, and 3) merging the neighboring regions, which have similar intensity values.

Manuscript received July 11, 2004. The Council of Scientific and Industrial Research, New Delhi, India provides the financial assistance for this work.

Ashish Thakur is with Department of Electrical Engineering, Indian Institute of Technology, Roorkee, Roorkee – 247 667, India. (e-mail: ashitdee@iitr.ernet.in).

*Radhey Shyam Anand is with Department of Electrical Engineering, Indian Institute of Technology, Roorkee, Roorkee – 247 667, India. (phone: 91-1332-285590; fax: 91-1332-273560; e-mail: anandfee@iitr.ernet.in).

II. ALGORITHM

A. Lookup table preparation

Let $X = [x_{i,j}]$, $i = 1,2,3,\ldots,M$ and $j = 1,2,3,\ldots,N$ be the image containing M rows and N columns with grey level $x_{i,j}$ at pixel (i,j). A region $W_{(w \times w)}$ of X is a connected subset of X. $W_{i,j}$ is to identify a local region associated with (i,j). The two local statistical parameters, the arithmetic mean $\mu_{i,j}$ and the variance $\sigma^2_{i,j}$ of image intensities, to be computed within a region are given by

$$\mu_{i,j} = \frac{1}{w^2} \sum_{m=-w/2}^{w/2} \sum_{m=-w/2}^{w/2} (x_{i-m,j-n}) \tag{1}$$

$$\sigma^2_{i,j} = \frac{1}{w^2} \sum_{m=-w/2}^{w/2} \sum_{m=-w/2}^{w/2} (x_{i-m,j-n} - \mu_{i,j})^2 \tag{2}$$

According to (1) and (2), a parameter representing the ratio of the local variance to the mean of the pixel (i,j) in (3) is calculated as following:

$$\alpha(i,j) = \frac{\sigma^2_{i,j}}{\mu_{i,j}} \tag{3}$$

The local variance and mean ratio of the granularity in the fully developed ultrasound speckle image is used as the measured parameter [10]. According to this parameter, it is possible to decide whether the processed pixel is within homogeneous region or not. In general, if the local variance to mean ratio is larger than that of speckle, then the corresponding pixel can be considered as a resolvable object. Otherwise, it belongs to a homogeneous region. The shape of speckle pattern and average speckle size varies at different locations of sectored images. Therefore, it is highly desirable to arbitrarily defined shape and size of the homogeneous regions for smoothing. This is achieved through the region growing procedure, which effectively fits the grown region to the homogeneous area without imposing any shape constraint. The region growing procedure employs a look-up table consisting of statistical bounds for different values of local statistics [11] [12].

B. Region growing method

The aim of region-based segmentation techniques is to extract the homogeneous zones from the ultrasound filtered image. Region growing technique is generally better in noisy images, where borders are extremely difficult to detect such as ultrasound medical images. For region growing method homogeneity is an important property, which can be based on gray-level, shape, model, etc [13]. For region- based segmentation, the basic requirement to satisfy the region similarity in an image is as follows:

$$H(R_I) = TRUE \qquad i = 1,2,3,\ldots\ldots,P \tag{4}$$

where P is the total number of regions in an image and $H(R_i)$ is a binary homogeneity evaluation of the region R_i. A logical statement represented by (4) gives that if pixels in the region are sufficiently similar in terms of grey level, then it is true. It means

$$H(R_I) = \begin{cases} TRUE & if\,|f(j,k) - f(m,n)| \le T \\ FALSE & Otherwise \end{cases} \tag{5}$$

where (j,k) and (m,n) are the coordinates of neighboring pixels in region R. This predicate state that a region R is uniform if and only if any two neighboring pixels differ in grey level by no more than T. Using this equation a common misconception is involved such as it restricts the grey level variation within a region to a range of width T [14]. A similar predicate can be used that

$$H(R_I) = \begin{cases} TRUE & if\,|f(j,k) - \mu_R| \le T \\ FALSE & Otherwise \end{cases} \tag{6}$$

where $f(j,k)$ is the grey level of a pixels from region R with coordinates (j,k) and μ_R is mean grey level of all pixel in R except the pixel at (j,k). The region similarity criteria shown in (5) and (6) are basically known as fixed threshold homogeneity test.

In this paper, the seeded region growing approach is used which segment the image into the homogeneous regions with respect to a set of seed points. The basic approach is to start with each image pixels which are taken as a set of seed points and these grow regions by appending to each seed those neighboring pixels that have properties similar to the seed. The selection of the similarity criteria for region growing is shown in (7).

$$\alpha(i,j) - \beta(i,j) \le \alpha(m,n) \le \alpha(i,j) + \beta(i,j) \tag{7}$$

where $\beta(i,j)$ is the statistical similarity bound shown in (8) and *a, b* and *c* are the coefficients with values that are estimated empirically.

$$\beta(i,j) = a + be^{-c\alpha(i,j)} \tag{8}$$

The local statistics $\alpha(i,j)$ are used as the quantitative measure to obtain a homogeneous region for each image pixel. But the size and shape of the homogeneous region are not controlled by the spatial distance bound, but are controlled by the region merging criteria.

C. *Region merging criteria*

The most natural method of region growing is to begin the growth in the raw image data, where each pixel representing a single region. These regions almost certainly do not satisfy the condition for the hypothesis in (4), and so regions will be merged as long as remains satisfied in (9).

$$H(R_i \cup R_j) = FALSE \qquad i \neq j \quad R_i \text{ is adjacent to } R_j \qquad (9)$$

This approach takes into consideration of merging adjacent regions based on the probability that they have the same statistical distribution of intensity values. The region merging starts from a uniform seed region and neighbors are merged until no more neighboring regions conform to the uniformity criterion. At this point, the region is extracted from the image, and a further seed is used to merge another region [13].

In this paper, the neighboring region obtained from the region growing procedure, with similar intensity values are merged. In this procedure every homogeneous regions are identified and labeled by unique number. The labeling of the regions is implemented through the 8-connectivity region labeling technique. Let the homogeneous region of an pixel located at (i,j), be labeled by $K_{i,j}$ and total number of the pixels into that region is $Q_{i,j.}$ If $Q_{i,j} < B$, then $K_{i,j}$ is not merged with the neighboring regions. Otherwise, each region $K_{m,n}$ neighboring the region $K_{i,j}$ is merged to the region $K_{i,j}$. The merging criteria satisfying the condition expressed in (10) is as follows:

$$\mu(i,j) - \Delta\mu \le \mu(m,n) \le \mu(i.j) + \Delta\mu \qquad (10)$$

where $\mu(i,j)$ is the mean intensity value in the region $K_{i,j}$, B and $\Delta\mu$ are the positive constants representing the bounds for number of the pixels and gray level intensity, respectively. The algorithm is summarized as under:

1) Choose a window sized $(2k+1)$ x $(2k+1)$ being centered at (i,j).
2) Generate the look up table for local statistics for each pixel:
   a) Calculate the homogeneity $\alpha(i,j)$ of $W_{i,j}$.
   b) Calculate the statistical similarity bound $\beta(i,j)$ of every $\alpha(i,j)$.
3) Implement region growing for every pixel
   a) Each image pixel is taken as a seed pixel
   b) Store the neighboring pixel information for every seed point
   c) Grow region from the seed point according to the statistical similarity criterion
4) Implement region merging
   a) Labeling the each region with a unique number.
   b) Store the neighboring region information for every seed region
   c) Merge the neighboring region according to the merging criteria with the seed region. The parameter for this criteria are $\Delta\mu$ and B.
   d) Update the segmented image output.

III. Experimental Results and Discussions

The proposed local statistical based region growing method for segmentation is applied to B-mode ultrasound images of breast mass shown in Fig. 1 and liver cyst image shown in Fig. 2. In the sequel, the result of the region growing and merging procedure is presented. In Fig. 3 (a-f) and Fig. 4 (a-f), the initial homogeneous regions from the growing step are shown, where the coefficient parameters (*a, b,* and *c*) for the statistical similarity bound of (8), are chosen in the range between 0.001 to 0.009 for *a*, 0.01 to 0.09 for *b*, and 10 to 100 for *c*, with square window size = 11 x 11.

In Fig. 3, the result obtained from different values of statistical similarity bound for breast mass image is shown. Here, the higher value of $a = 0.009$ and $b = 0.08$ and minimum value of $c = 10$ produces less trivial regions and reduce over segmentation. Similarly, in Fig. 4, $a = 0.004$ and $c = 30$ reduce over segmentation. Next, the initial region growing images are smoothed by the merging of neighboring regions for resolving the details using $\Delta\mu$ and B. The values of $\Delta\mu$ are 5 and 10 for breast image and liver image, respectively. The value of B is 40 and 20 for breast and liver image, respectively. The final output images with smoothed region are shown in Fig. 5 (a-f) and Fig. 6 (a-f) according to value of *a, b, c,* $\Delta\mu$ and *B*.

IV. Conclusions

A local statistics based segmentation procedure has been developed for ultrasound medical images. The homogeneous regions in the ultrasound images are preserved and controlled by the look up table consisting of homogeneity criteria and statistical similarity bound for different values of local statistics of each pixel. The window size used for computation of local statistics is chosen as 11 x 11. This choice is basically based on the small homogeneous regions, which are produced by the granularity. The window size must be large enough for the measurement of homogeneity region criteria and statistical similarity bound. The selection of parameters of the similarity bound depends on the granularity or speckle into the images. The initial growing region shows the large number of false homogeneous region into the image, which was joined with their neighboring region by merging. The parameters for merging criteria depend on the high frequency artifacts such as over segmentation.

This algorithm can be used for fully developed speckle ultrasound images with efficient segmentation. The merged regions reduce over segmentation without using further smoothing into the image. The final segmentation results exhibit accurate homogeneous regions without implementing texture-based analysis.

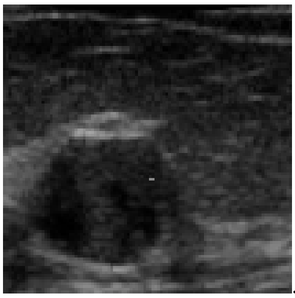


Figure 1. Ultrasound medical image for breast mass

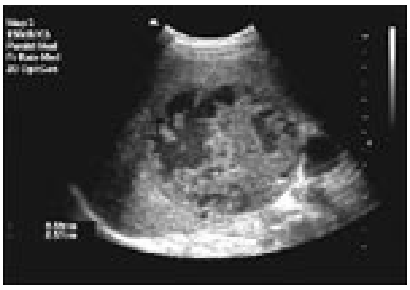
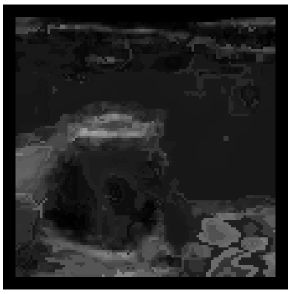
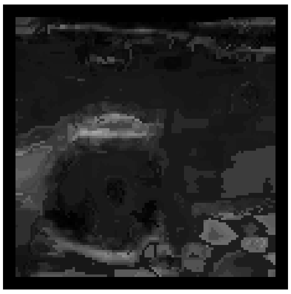


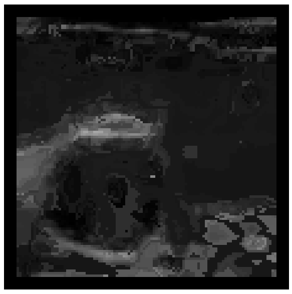
Figure 2. Ultrasound medical image for liver cyst



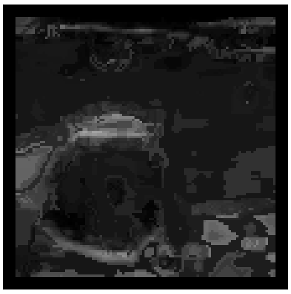
(a) a =0.004, b =0.05, c =20



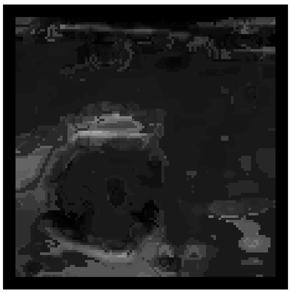
(b) a =0.005, b =0.07, c =20



(c) a =0.006, b =0.05, c =20



(d) a =0.007, b =0.07, c =20



(e) a =0.008, b =0.08, c =20

(f) a =0.009, b =0.08, c =10

Figure 3 (a-f). Initial region growing results for breast mass image.

(a) a =0.001, b =0.05, c =10

(b) a =0.002, b =0.01, c =10

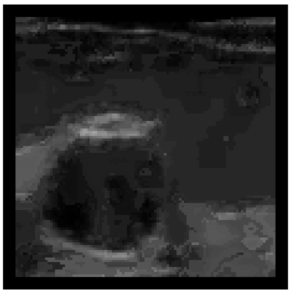
(c) a =0.002, b =0.03, c =10

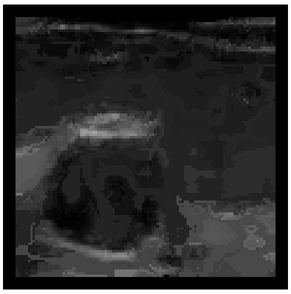
(d) a =0.002, b =0.05, c =30


(e) a =0.004, b =0.03, c =10

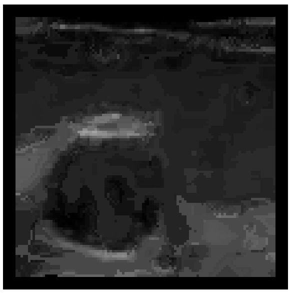

(f) a =0.004, b =0.03, c =30

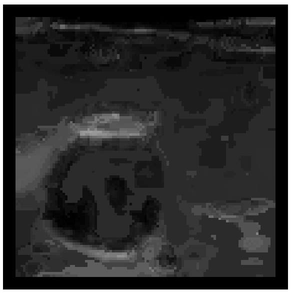
Figure 4 (a-f). Initial region growing results for liver cyst image.


(a)


(b)


(c)


(d)


(e)

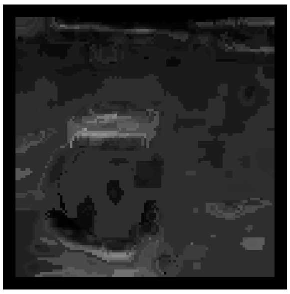

(f)

Figure 5 (a-f). Final segmented results for breast mass image after Fig. 3 (a-f) with $\Delta\mu = 5$ and $B = 40$.

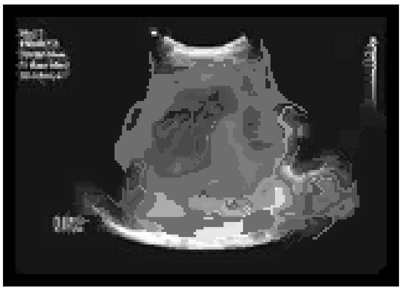

(a)


(b)

International Journal of Medical, Medicine and Health Sciences
ISSN: 2517-9969
Vol:1, No:10, 2007

(c)

(d)



(e)

(f)

Figure 6 (a-f). Final segmented results for liver cyst image after Fig. 4 (a-f) with $\Delta\mu = 10$ and $B = 20$.

ACKNOWLEDGMENT

The authors are thankful to the Department of Electrical Engineering, Indian Institute of Technology, Roorkee, for providing the required computational and experimental facilities.

REFERENCES

[1] Hiransakolwong, N., Hua, K. A., Vu, K., and Windyga, P. S. (2003) Segmentation of ultrasound liver images: An automatic approach. IEEE Multimedia and Expo, 2003 ICME 03. Proceedings, 2003 International Conference, 1, 573 -576.

[2] Gonzalez, R. C. and Wintz, P. (2002) Digital Image Processing, 2nd ed., Pearson Education (Singapore) Pte. Ltd. Delhi, India.

[3] Pavlidis, T. (1977) Structural Pattern Recognition, Springer-Verlag, Berlin, Heidelberg.

[4] Zhu, S.C., and Yuille, A. (1996) Region competition: Unifying snakes, region growing, and bayes/MDL for multiband image segmentation, IEEE Transaction on Pattern Analysis and Machine Intelligence, 18, 884-900.

[5] Pavlidis, T., and Liow, Y. T. (1990) Integrating region growing and edge detection , IEEE Transaction on Pattern Analysis and Machine Intelligence, 12, 225-231.

[6] McInerney, T., and Terzopoulos, D. (1996) Deformable models in medical image analysis: a survey, Medical Image Analysis, 1, 91-108.

[7] Adams, R., and Bischof, L. (1994) Seeded region growing. IEEE Transaction on Pattern Analysis and Machine Vision, 16, 641-647.

[8] Vincent, L., and Soille, P. (1991) Watersheds in digital spaces: An efficient algorithm based on immersion simulation. IEEE Transaction on Pattern Analysis and Machine Intelligence, 13, 583-598.

[9] Hao, X., and Gao, S. (1999) A novel multi scale nonlinear thresholding method for ultrasonic speckle suppressing, IEEE Transactions on Medical Imaging, 18, 787-794.

[10] Loupas, T., McDicken, W. N., and Allan, P.L. (1989) An adaptive weighted median filter for speckle suppression in medical ultrasonic images, IEEE Transaction on Circuits Systems, 36, 129-135.

[11] Karaman, M., Kutay, M. A. and Bozdagi, G. (1995) adaptive speckle suppression filter for medical ultrasonic imaging. IEEE Transactions on Medical Imaging, 14, 283–292.

[12] Y. Chen, Y., Yin, R. Flynn, P., and Broschat, S. (2003) Aggressive region growing for speckle reduction in ultrasound images. Pattern Recognition Letters, 24, 677-691.

[13] Sonka, M., Hlavac, V., and Boyle, R. (1991) Image Processing, Analysis and Machine Vision. 2nd ed. Pacific Grove, CA: PWS.

[14] Efford, N. (2000) Digital Image Processing Using JAVA, 1st ed., Addison Wesley Professional.

Ashish Thakur received B.E. degree in Electronics and Instrumentation Engineering from S.A.T.I, Vidisha, Barkaullah University, Bhopal, India in 1997 and M.E. degree in Electrical Engineering from R.G.P.V.V. Bhopal, India in 2001. He worked in industry from 1997 to 1999 as graphics design engineer. He was faculty in the Dept. of Electronics and Communication Engineering, SGSITS, Indore, India from 2001 to 2002. Currently, he is working for his PhD in the Department of Electrical Engineering, IIT Roorkee, India. His research areas of interest are medical image processing and digital signal processing.

Radhey Shyam Anand received B.E., M.E. and Ph.D. Degrees in Electrical Engineering from University of Roorkee (now Indian Institute of Technology, Roorkee), India in 1985, 1987 and 1992, respectively. He joined Electrical Engineering Department of IIT Roorkee as Assistant Professor in June 1998. Previous to IIT Roorkee he has been the lecturer at IIT Kharagpur, India for about four years. His research areas of interest are microprocessor & computer based instrumentation, biomedical signals and image processing, and ultrasonic applications in non-destructive evaluation and medical diagnosis. He is life member of Ultrasonic Society of India.