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A Comparitive Survey Of Various Segmentation Techniques

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Abstract:

Segmentation or the delineation of object boundaries in medical images remains a necessary step to obtain qualitative and quantitative measurements. Among these images, Ultrasound images plays a crucial role because the acquisition of these images is non invasive, cheap and does not require ionizing radiations compared to other medical imaging techniques. Due to acoustic interferences and artifacts, the automatic segmentation of anatomical structures in ultrasound imagery becomes a real challenge. Thus, to enhance the capabilities of ultrasound as a qualitative tool in clinical medicine, here we discuss the ultrasound image segmentation methods, focusing on techniques developed for medical. First, we discuss the formation of ultrasound images and conventional methods of image segmentation. After that we present the formulated methods for ultrasound image segmentation concerning the three largest areas of ultrasound imaging. Next section explains the validation degree that has been done in different application areas of ultrasound. In last section we conclude by referencing some papers which have introduced original ideas that exhibited particular usefulness in clinical domain specific to the ultrasound segmentation problem.

Keywords: *Segmentation; Ultrasound; Speckle Noise; Artifacts; Ionizing radiations*

1. Introduction

Processing of images by computer with the goal of finding what objects are presented in the image known as image analysis. Image segmentation is one of the most critical tasks in automatic image analysis. Ultrasound imaging is arguably the hardest medical imaging modality upon which to perform segmentation. Attenuation, speckle, shadows and signal dropout can result in missing or diffused boundaries. Also, the contrast between areas of interest is often low. Despite these factors, ultrasound imaging still remains an important tool for clinical applications and any effort to improve segmentation of these images is highly desirable.In a standard ultrasound system there are three basic types of data available for analysis: radiofrequency (RF) signals, envelope-detected signals, and B-mode images. A transmit/receive ultrasound transducer receives multiple analogue radio-frequency (RF) signals which are converted to digital RF signals and beam formed into a single RF signal. The RF signal is then filtered, and envelope detection is performed to give an envelope detected signal. Finally, the envelope-detected signal undergoes log compression, and often proprietary post-processing is applied to give a grayscale representation. The resulting signals are then interpolated and rasterized to give a B-mode or display image[1].

2. Conventional Methods Of Image Segmentation

2.1.Gray Level Discontinuity / Edge based Approaches

In discontinuity-based approach, the partitions or sub-division of an image is based on some abrupt changes in the intensity level of images. Since isolated points and lines of unitary pixel thickness are infrequent in most practical application, edge detection is the most common approach in gray level discontinuity segmentation. An edge is a boundary between two regions having distinct intensity level. It is very useful in detecting of discontinuity in an image. When the image changes from dark to white or vice-versa.

2.2 Gray Level Similarity / Region Based Approaches

Similar according to predefined Criterion

2.2.1.Region-Oriented Segmentation

Basic rules of region oriented segmentation are as follows:

Let R be the entire image region. Then by using segmentation algorithm the image region R is subdivided into ‘n’ subregions R1,R2,……, Rn, such that….

- $\bigcup_{i=1}^{n} R_i = R$
- R_i is a connected region, i = 1, 2, . . . , n
- $R_i \cap R_j = \emptyset$ for all i and j, where i≠j
- p(R_i) TRUE for i = 1,2,…..,n
- $P(R_i \cup R_j)$ = FALSE, where i≠j
-

Here P(Ri) is logical homogeneity predicate defined over all points in Rj

- Every pixel must be in a region
- All the points in a region must be “connected”
- Regions must be disjoint
- For example P(Ri) = TRUE if all the pixels in Ri have the same gray level
- Regions Ri and Rj are different in some sense

2.3.Region Growing

The first step in region growing is to select a set of seed points. Seed point selection is based on some homogeneity criterion (for example, pixels in a certain gray-level range, pixels evenly spaced on a grid, etc.). The initial region begins as the exact location of these seeds. The regions are then grown from these seed points to adjacent points depending on a region membership criterion. The criterion could be, for example, pixel intensity, gray level texture, or color.

2.4.Region Splitting And Merging

In this technique an image is initially divided into a set of arbitrary subimages of disjoint regions, and then merge and / or split operations are carried out based on certain criteria. The split and merge algorithm is as follows:

- Split into four disjoint quadrants any region Ri for which
  - $p(R_i)$ = FALSE
- Merge any adjacent regions R_i and R_k for which
  - $P(R_i \cup R_k)$ = FALSE
- Stop when no further merging or splitting is possible

2.5.Split And Merge

Define $p(R_i)$ = TRUE if at least 80% of the pixels in Ri have the property |zi – mi| < 2σi. If $p(R_i)$ = TRUE the value of all the pixels in Ri are set equal to mi Splitting and merging are done using the algorithm on the previous transparency Properties based on mean and standard deviation attempt to quantify the texture of a region Texture segmentation is based on using measures of texture for the predicates P(Ri). Segmentation algorithms have had fairly limited application in ultrasound imaging. High levels of speckling present in ultrasound images make accurate segmentations difficult. Furthermore, the real-time acquisition in ultrasound makes it better suited for motion estimation tasks ([3, 4]) where active contours, because of their dynamic nature, are often used. Ultrasound is also often employed in detecting pathology using textural classifiers [5] but regions of interest are typically obtained through manual interaction. Nevertheless, some automated segmentation work has been performed in ultrasound for extracting a variety of structures. In [6], a thresholding of intensity and texture statistics was used to segment ovarian cysts. Deformable models have had good success in ultrasound applications such as in the segmentation of echocardiograms [7, 8, 9]. In [10], an active contour was used to determine the boundary of the calcaneus in broadband ultrasonic attenuation parameter images, which are less noisy than standard ultrasound images. In [12] deformable models were used to determine the boundary of the fetus and the fetus head respectively. Deformable models have also been used to segment cysts in ultrasound breast images [14]. Other methods have been applied for the segmentation of coronary arteries in intravascular ultrasound images [13] and for segmenting the pubic arch in transrectal ultrasound [11].

2.5.1.<u>Segmentation Using Threshold</u>

Threshold technique is one of the important techniques in image segmentation Thresholding can be viewed as:

T = T[x, y, p(x, y), f(x, y)]

Where f(x, y) is gray-level at (x, y) and p(x, y) denotes some local property, for example average gray level in neighborhood.

A thresholded image g(x, y) is defined as

g(x, y)= {1, f(x, y) >T}

g(x, y)= { 0, f(x, y) < T}

where 1 is object and 0 is background

When T = T[f(x, y)], threshold is global

When T = T[p(x, y), f(x, y)], threshold is local

When T = T[x, y, p(x, y), f(x, y)], threshold is dynamic.

3. Formulated Methods For Segmentation And Their Applications In US Imaging

N.Friedland et al. [16] developed an automatic algorithm for detection of cavity boundaries with high speed in 2-D echocardiograms using an optimization algorithm called simulated annealing (SA). The novelty of the algorithm is the implementation of the simulated annealing optimization method in detecting ultrasound image cavity boundaries from a sequence of input images. Although the global minimum may theoretically not be found in finite time using **SA,** frieland's experience with this problem shows satisfactory convergence with relatively inexpensive computational cost, even for a sequential implementation. SA also allowed the utilization of an**64** member cyclic Markov random field (MRF), which yields design flexibility in the selection of a heuristic decision rule. This rule, which is a unique feature of the algorithm, took into account a number of physical and geometrical properties of echocardiographic cavities from sequential input images. All of the energy function elements simultaneously participated in the determination of the boundary points' location. The approach freed the system from interactive operator dependence. The algorithm attained a high level of success in overcoming speckle effects. Boundary speckles were joined into a continuous cavity border and random speckles were ignored in the detection.

Binder et al. [17] employed a two-layer back propagation network that was trained by manually identifying 369 sample regions(7× 7 pixels) from eight training images to segment the image as tissue(n= 279) or blood pool(n = 90) . Parameters (gray level mean and variance, contrast, entropy, and homogeneity from the co-occurrence matrices) were used in the ANN. Endocardial borders were found by first performing a radial search for candidate border points in single frames and then using a spatio-temporal contour linking step. The method was applied to end-diastolic and end-systolic parasternal SAX images from 38 patients with the data being of variable quality (12 good, 13 moderate, and 13 poor). This is one of the few studies that has explicitly looked at data of varying quality. Segmentation was successful in 34 of the 38 datasets. The automated method was compared with manual tracing by two experts. The ANN showed good correlation(r = 0.99) but from Bland–Altman analysis tended to overestimate the cavity areas. Technetium radionuclide ventriculography (Tc-RNV) was performed on 12 patients to enable the ejection fraction to be compared. The automated system showed a correlation r = 0.93 of with Bland–Altman analysis showing that the ANN overestimated the ejection fraction. Over all the analyses, the best correlations were with the best data.

Mishra et al. [15] proposed an active contour solution where the optimization was performed using a genetic algorithm. In a first image, low pass filtering and morphological operations were used to define an initial estimate of the contour. A nonlinear mapping of the intensity gradient was used in the energy functional which is minimized. The final contour was used to initialize contour finding in the next time frame. The convergence of the method was compared to solving the active contour using the conventional constrained quasi-Newton method. Manual delineations were done on 20 frames by two experts and the average compared to the automated algorithm to show that the intervariability between experts was similar to the difference between the manual and automated methods. The area correlation was found to be 0.92. This was a preliminary evaluation from which strong conclusions cannot be drawn.

Level sets are often considered as an alternative to active contours and this approach has also been considered for Echocardiographic image segmentation. Yan et al. [18] considered applying the level set method to echocardiographic images using an adaptation of the fast marching method. To reduce errors attributed to using local feature (intensity gradient) measurements, they used an average intensity gradient-based measure in the speed term. The method was applied to a parasternal short axis and an apical four-chamber view sequence but the results were only discussed qualitatively.

Mignotte and Meunier [19] chose to use a statistical external energy in a discrete active contour for the segmentation of short axis parasternal images, arguing that this was well-suited in ultrasound images with significant noise and missing boundaries. To this end, a shifted Rayleigh distribution was used to model gray levels statistics.

Chalana et al. developed a multiple active contour method to detect both the endocardium and epicardium in short-axis views [20]. They defined the left ventricle by an active surface model, which they reparameterized to show that the surface could be represented by two planar curves representing the Endocardial and epicardial borders. They used the image intensity gradient as the attracting force and invoked temporal continuity via an external energy term that constrained the motion between consecutive frames. Their method was validated on 44 clinical datasets against manual delineations by four experts. The area correlation coefficient between their method and the average manual outline was 0.95 for the epicardium and 0.91 for the endocardium. They reported that the computer algorithm gives a lower boundary difference error for the epicardium than the endocardium. This may be due to the fact that their algorithm was initialized with a manual delineation of the epicardium.

A 2-D semi-automatic discrete dynamic contour (DDC) model for prostate boundary segmentation was proposed by Ladak et al. [22] based on the Lobregt and Viergever model [23]. This model used four (for 2-D, six for 3-D) manually selected points on specific locations of the prostate boundary and then applied an appropriate interpolation to complete the initial model.

Knoll et al. [21] proposed employing a parametrization of a snake based on a 1-D dyadic wavelet transform as a multiscale boundary curve analysis tool. The initialization of the snake used template matching between contour models of a training set and significant image edges. The authors used a 1-D wavelet based method in order to constrain the shape of the snake to evolve towards predefined models. The contour deformation method was integrated in a coarse-to-fine segmentation framework based on multiscale image edges represented by the modulus maxima of the 2-D dyadic wavelet transform. The fully automatic method was tested on 77 images from 11 patients against two experts. The analysis showed that shape information slightly improves results. However, no statistical analysis (of significance nor variance) was shown for the error comparison against the inter-observer variability.

Yu et al. [24] presented a two-step semi-automatic active contour based segmentation method. First, an initial elliptical approximation of the contour was obtained using two manually selected points. A rough binary segmentation was then obtained by optimizing an area-weighted mean-difference criterion in a level sets framework. Finally, a finer segmentation was fulfilled in a polar coordinate system through use of parametric active contour model.

The studies of Stavos et al. [25]–[27] have greatly influenced the design of algorithms for breast mass detection. Interestingly, no significant work has looked at the screening case, i.e., most work has assumed the presence of a, typically single, suspicious mass.

Horsch et al. [28] presented a method involving Thresholding a preprocessed image that has enhanced mass structures. Comparison is made of a partially automatic and fully automatic version of the method with manual delineation on 400 cases/757 images (124 "complex" cysts, 182 benign masses, and 94 malignant masses). They compute four image-based features (shape, echogeneity, margin, and posterior acoustic behavior) defined respectively in terms of the depth-to-width ratio, auto correlation, "normalized radial gradient," and comparison of gray levels, to test their effectiveness at distinguishing malignant and benign masses.

Chen et al. [29] presented a NN approach where input features were variance contrast, autocorrelation contrast, and the distribution distortion in the (Daubechies) wavelet coefficients and an multilayered perceptron neural (MLP) network with one hidden layer was trained by error back propagation. The method was applied to a database of 242 cases (161 benign, 81 carcinoma) giving a sensitivity of 98.77% and specificity of 81.77%. They strongly argued that image texture was an important component that made their method successful.

Xiao et al. [30] presented an expectation-maximization method that simultaneously estimates the attenuation field at the same time as classification of regions into different (intensity-based) regions. The number of regions (classes) needs to be specified, which in the intended application is not a strong limitation. That method was tested on experimental data with different time gain compensation (TGC) settings to show that their approach gave consistent segmentations under different TGC settings but has not undergone a large clinical assessment.

4. Validation

Table No. 1 summarize the validation done on principal methods discussed in section third concerning the three largest areas of application of ultrasound image segmentation, namely cardiology, breast cancer and prostate cancer.

4.1.Key To Table

- Modality: 2-D, 2-D+T , SAX = Short Axis, LAX = Long Axis
- Segmentation Criteria: C = Contour, Region (2-D)
- Ad hoc parameters: (N) none or sensitivity analysis done,(Y/N) yes and some attempt at sensitivity analysis, (Y) yes and no sensitivity done.
- Automation: (Y) full, (N) interactive guidance/correction

5. Conclusion

Here we discussed the formation of Ultrasound Images and there advantages in medical field. Because of increasing applications in the field of ultrasound images in diagnosis as well as therapeutic purposes we need to enhance the feature which we require for further processing. There are different techniques for doing this. One of these is segmentation which is a wide area of image processing. So in the other section we briefly discussed the New Segmentation methods.

In 1989, a method was developed for detection of cavity boundaries in 2D echocardiograms which freed system from interactive operator dependence and also got success in overcoming speckle effects. An active contour solution proposed in 2003, where optimization was performed using a Genetic Algorithm. In the same year, level sets are considered as an alternative to active contours. They used an average intensity gradient based measure in speed term. In 2000, a 2D semi-automatic discrete dynamic contour model for prostate boundary segmentation was introduced and attained high level success. Similarly, as time goes many researchers introduced methods in specific application areas of ultrasound. The Table differentiates the methods of US segmentation of any particular clinical domain on the basis of segmentation criteria, such that few are using contour based seg. and others region based.

We have seen the need for more effort on segmentation validation to better understand the strengths and limitations of methods both through comparison with other methods in the literature and on larger (ideally standard) databases of data. This is important to encourage the adoption of methods in clinical practice.

Reference	Year	Modality	Seg. criteria	Ad hoc Parameters	Automation	Interaction type
Friedland [15]	1989	LAX 2D	C	(Y/N)	(N)	
Binder [16]	1999	SAX	R	(Y)	(N)	ROI, Manual training
Mishra [17]	2003	SAX	C	(Y)	(N)	ROI
Yan [18]	2003	SAX 4C	C	(Y)	(N)	Seed Point
Mignotte [19]	2001	SAX	C/R	(Y)	(Y)	
Chalana [20]	1996	SAX	2D+T C	(Y/N)	(N)	ROI, Manual initial
Knoll [21]	1999	2D	C	(Y)	(N)	
Ladak [22]	2000	2D	C	(Y)	(N)	Manual initial(4 points) Manual correction
Yu [24]	2004	2D	C/R	(Y/N)	(N)	ROI, Manual initial
Chen [29]	2002	2D B-mode	R	(Y)	(N)	ROI specified
Horsch [28]	2001,2002	2D B-mode	R	(Y)	(Y/N)	Lesion center
Xiao [30]	2002	2D B-mode	R	(N)	(Y)	

Table 1

6. Reference

1. J A Noble "Ultrasound image segmentation and tissue characterization" Part H: J. Engineering in Medicine, Vol. 223, PP. 1-10, June 2009.
2. Hill, C. R., Bamber, J. C., and ter Haar, G. R. "Physical principles of medical ultrasonics", 2nd edition, 2004 (John Wiley, Chichester, UK).
3. J.M.B. Dias and J.M.N. Leitao. "Wall position and thickness estimation from sequences of echocardiographic" images. IEEE T. Med. Imag., 15:25–38, 1996.
4. I. Mikic, S. Krucinski, and J.D. Thomas. "Segmentation and tracking in echocardiographic sequences: active contours guided by optical flow estimates" IEEE T. Med. Imag., 17:274–284, 1998.
5. A. Mojsilovic, M.V. Popovic, A.N. Neskovic, and A.D. Popovicq. "Wavelet image extension foranalysis and classifcation of infarcted myocardial tissue", IEEE T. Biomed. Eng., 44:856–866, 1997.
6. Y. Zimmerand R. Tepper and S. Akselrod. A two-dimensional extension of minimum cross entropy thresholding for the segmentation of ultrasound images. Ultrasound Med. Biol., 22:1183–1190, 1996
7. G. Coppini, R. Poli, and G. Valli. Recovery of the 3-D shape of the left ventricle from Echocardiographic images. IEEE T. Med. Imag., 14:301–317, 1995.
8. T.N. Jones and D.N. Metaxas. Segmentation using deformable models with affinity-based localization. Lecture Notes in Computer Science, 1205:53–52, 1997.
9. D. Kucera and R.W. Martin. Segmentation of sequences of echocardiographic images using a simplified 3D active contour model with region based external forces. Comput. Med. Im. Graph., 21:1–21, 1997.
10. F. Lefebvre, G.Berger, and P. Laugier. Automatic detection of the boundary of the calcaneus from ultrasound parametric images using an active contour model: clinical assessment. IEEE T. Med. Imag., 17:45–52, 1998.
11. S.D. Pathak, P.D. Grimm, V. Chalana, and Y. Kim. Pubic arch detection in transrectal ultrasound guided prostate cancer therapy. IEEE T. Med. Imag., 17:762–771, 1998.
12. S.D. Pathak, V.Chalana, and Y.M. Kim. Interactive automatic fetal head measurements from ultrasound images using multimedia computer

technology. Ultrasound in Medicine and Biology, 23:665–673, 1997.

13. M. Sonka, X. Zhang, M. Siebes, M.S. Bissing, S.C. DeJong, S.M Collins, and C.R. McKay. Segmentation of intravascular ultrasound images: a knowledge-based approach. IEEE T. Med. Imag., 14:719–732, 1995.
14. A. Yezzi, S. Kichenassamy, A. Kumar, P. Olver, and A. Tannenbaum. A geometric snake model for segmentation of medical imagery. IEEE T. Med. Imag., 16:199–209, 1997.
15. A. Mishra, P. K. Dutta, and M. K. Ghosh, "A GA based approach for boundary detection of left ventricle with echocardiographic image sequences," Image Vis. Comput., vol. 21, pp. 967–976, 2003.
16. N. Friedland and D. Adam, "Automatic ventricular cavity boundary detection from sequential ultrasound images using simulated anneal," IEEE Trans. Med. Imag., vol. 8, no. 4, pp. 344–353, Dec. 1989.
17. T. Binder, M. Sussner, D. Moertl, H. Strohmer, T. Baumgartner, G. Maurer, and G. Porenta, "Artificial neural networks and spatial temporal contour linking for automated endocardial contour detection on echocardiograms: A novel approach to determine left ventricular contractile function," Ultrasound Med. Biol, vol. 25, no. 7, pp. 1069–1076, Sept. 1999.
18. J. Y. Yan and T. Zhuang, "Applying improved fast marching method to endocardial boundary detection in echocardiographic images," Pattern Recognit. Lett., vol. 24, no. 15, pp. 2777–2784, Nov. 2003.
19. M. Mignotte and J. Meunier, "A multiscale optimization approach for the dynamic contour-based boundary detection issue," Comput. Med. Imag. Graph., vol. 25, no. 3, pp. 265–275, May–Jun. 2001.
20. V. Chalana, D. T. Linker,D. R. Haynor, and Y. Kim, "A multiple active contour model for cardiac boundary detection on echocardiographic sequences," IEEE Trans. Med. Imag., vol. 15, no. 3, pp. 290–298, Jun. 1996.
21. C. Knoll, M. Alcaniz, V. Grau, C. Monserrat, and M. Carmen Juan, "Outlining of the prostate using snakes with shape restrictions based on the wavelet transform," Pattern Recognit., vol. 32, no. 10, pp. 1767–1781, Oct. 1999.
22. H. M. Ladak, F. Mao, Y. Q. Wang, D. B. Downey, A. Steinman, and D. A. Fenster, "Prostate boundary segmentation from 2-D ultrasound images," Med. Phys., vol. 27, no. 8, pp. 1777–1788, Aug. 2000.
23. S. Lobregt and M. A. Viergever, "A discrete dynamic contour model," IEEE Trans. Med. Imag., vol. 14, no. 1, pp. 12–24, Mar. 1995.

24. Y. Yu, J. A. Molloy, and S. T. Acton, “Segmentation of the prostate from suprapubic ultrasound images,” Med. Phys., vol. 31, no. 12, pp. 3474–3484, Dec. 2004.
25. A. Stavos, D. Thickman, C. Rapp, M. Dennis, S. Parker, and S. G. A., “Solid breast modules: Use of sonography to distinguish between benign and malignant lesions,” Radiology, vol. 196, pp. 123–134, 1995.
26. V. Jackson, “Management of solid breast modules: What is the role of sonography?,” Radiology, vol. 196, pp. 14–15, 1995.
27. P. Arger,C. Sehgal, E. Conant, J. Zuckerman, S. Rowling, and J. Patton, “Interreader variability and predictive value of is descriptions of solid masses: Pilot study,” Acad. Radiol., vol. 8, pp. 335–342, 2001.
28. K. Horsch, M. L. Giger, L. A. Venta, and C. J. Vyborny, “Automatic segmentation of breast lesions on ultrasound,” Med. Phys., vol. 28, no. 8, pp. 1652–1659, Aug. 2001.
29. D. R. Chen, R. F. Chang, W. J. Kuo, M. C. Chen, and Y. L. Huang, “Diagnosis of breast tumors with sonographic texture analysis using wavelet transform and neural networks,” Ultrasound Med. Biol., vol. 28, no. 10, pp. 1301–1310, Oct. 2002.
30. G. F. Xiao, M. Brady, J. A. Noble, and Y. Y. Zhang, “Segmentation of ultrasound B-mode images with intensity inhomogeneity correction,” IEEE Trans. Med. Imag., vol. 21, no. 1, pp. 48–57, Jan. 2002.