

A comparative survey  
of various  
segmentation  
techniques health  
and social care es...



## **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 degree of validation that has been done in different clinical domains. Then, In last section we conclude by referencing some papers which have presented original ideas that have demonstrated particular clinical usefulness 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 <https://assignbuster.com/a-comparitive-survey-of-various-segmentation-techniques-health-and-social-care-essay/>

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**

Gray Level Discontinuity / Edge based Approaches : Edge detection is a well-developed field on its own within image processing. Region boundaries and edges are closely related, since there is often a sharp adjustment in intensity at the region boundaries. Edge detection techniques have therefore been used as the base of another segmentation technique. 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  $R_1, R_2, \dots, R_n$ , such that....(a)  $R_i$  is a connected region,  $i = 1, 2, \dots, n$ (c)

$\cap$

= for all  $i$  and  $j$ , where  $i \neq j$ (d)  $P_i(x, y)$  TRUE for  $i = 1, 2, \dots, n$ (e)  $P_j(x, y) =$  FALSE, where  $i \neq j$ Here  $P_i(x, y)$  is logical predicate defined over all points in  $R_i$ Every pixel must be in a regionAll the points in a region must be " connected" Regions must be disjointFor example  $P_i(x, y) =$  TRUE if all the pixels in  $R_i$  have the same gray levelRegions  $R_i$  and  $R_j$  are different in some sense

### Region growing

The first step in region growing is to select a set of seed points. Seed point selection is based on some user 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. Since the regions are grown on the basis of the criterion, the image information itself is important. For example, if the criterion were a pixel intensity threshold value, knowledge of the histogram of the image would be of use, as one could use it to determine a suitable threshold value for the region membership criterion.

## 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:(1) Split into four disjoint quadrants any region  $R_i$  for which  $\sigma_i = \text{FALSE}$ (2) Merge any adjacent regions and for which  $\sigma_i = \text{FALSE}$ (3) Stop when no further merging or splitting is possible

### Split and merge

Define  $\sigma_i = \text{TRUE}$  if at least 80% of the pixels in  $R_i$  have the property  $|z_i - m_i| < 2\sigma_i$ . If  $\sigma_i = \text{TRUE}$  the value of all the pixels in  $R_i$  are set equal to  $m_i$  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  $P(R_i)$ . 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. 2. 2 Segmentation using Threshold

Segmentation problems requiring multiple thresholds are best solved using region growing methods. 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 high speed detection of cavity boundaries in sequential 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 <https://assignbuster.com/a-comparitive-survey-of-various-segmentation-techniques-health-and-social-care-essay/>

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 ( $7 \times 7$  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

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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 <https://assignbuster.com/a-comparitive-survey-of-various-segmentation-techniques-health-and-social-care-essay/>



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

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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 accomplished via a parametric active contour model in a polar coordinate system. 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 <https://assignbuster.com/a-comparitive-survey-of-various-segmentation-techniques-health-and-social-care-essay/>

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.

KEY TO TABLE 📄 Modality: 2-D, 2-D+T , SAX = Short Axis, LAX = Long

AxisSegmentation 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

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## Conclusion

Here we discussed the formation of Ultrasound Images and their advantages in the medical field. Because of increasing applications in the field of ultrasound images in diagnosis as well as therapeutic purposes we need to enhance the features 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 the system from interactive operator dependence and also got success in overcoming speckle effects. An active contour solution was 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 terms. 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 by 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.

## **Table No. 1**

### **Reference**

### **Year**

### **Modality**

### **Seg. criteria**

### **Ad**

### **hoc**

### **Automation**

### **Interaction**

### **Parameters**

### **type**

### **Friedland**

1989LAX 2DC(Y/N)(N)

### **[15]**

### **Binder [16]**

1999SAXR(Y)(N)ROI, Manualtraining

### **Mishra [17]**

2003SAXC(Y)(N)ROI

### **Yan [18]**

2003SAX 4CC(Y)(N)Seed Point

### **Mignotte**

2001SAXC/R(Y)(Y)

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**[19]**

**Chalana**

1996SAX2D+T C(Y/N)(N)ROI,

**[20]**

Manualinitial

**Knoll [21]**

19992DC(Y)(N)

**Ladak [22]**

20002DC(Y)(N)Manualinitial(4points)Manualcorrection

**Yu [24]**

20042DC/R(Y/N)(N)ROI, Manualinitial

**Chen [29]**

20022D B-modeR(Y)(N)ROIspecified

**Horsch [28]**

2001, 20022D B-modeR(Y)(Y/N)LesioncenterXiao [30]20022D B-modeR(N)(Y)