Segmentation Of Uterine Fibroid Using Morphology: An Automatic Approach

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***Abstract*—Image segmentation is an important task in medical image analysis. Automatic segmentation of ultrasound image is a difficult task as it suffers from speckle noise. This paper presents a fully automatic approach in which there is no need for the user to provide a seed point to segment the image. It proposes a new method for segmenting the fibroid in uterus. The method used in this paper uses concepts in mathematical morphology. It completely avoids over segmentation which is a major problem in morphological segmentation. The performance of this method is also commendable.**

Keywords-morphology; regional minima; area open; segmentation; ultrasound

I. Introduction

Ultrasound imaging is widely used in the field of medicine. It is used for imaging soft tissues in organs like liver, kidney, spleen, uterus, heart, brain etc. In this paper automatic segmentation of uterine fibroid is performed. Fibroids are muscular tumors that grow in the wall of the uterus. Another medical term for fibroids is "leiomyoma" (leye-oh-meye-OH-muh) or just "myoma". Fibroids are almost always benign (not cancerous). Anyhow the symptoms caused by fibroid may cause certain inconvenience in women which needs to be treated. This paper deals with the segmentation of fibroid which is found inside the uterus. Calcified fibroid is a type of fibroid. The calcification will be shown in the ultrasound image as hyper echoic or white region. Ultrasound imaging is a common modality used for detecting fibroids. The most noticeable advantages of ultrasound scanning are safety, cost effectiveness, speed, easy handling and portability. The quality of ultrasound images is limited by granular speckle noise. This makes it difficult to segment the ultrasound images. In this paper the image is preprocessed to remove the speckle noise. We use a morphological cleaning algorithm to clean the image. Then the image is segmented by an algorithm which uses morphological concepts. Section II of this paper discusses the previous works available in the literature. Section III focuses on the preprocessing work of speckle noise removal. Section IV gives the morphological preprocessing algorithm used to remove the speckle noise in the image. Section V describes the proposed method of segmentation and the morphological concepts used in the method. Section VI is the proposed algorithm. Section VII focuses on the evaluation criteria which measures the validity of the proposed algorithm. Section VIII is about results and discussions. Section IX gives the conclusion.

II. Related Works

Various techniques for speckle noise removal are available in the literature [1-5]. There are many segmentation algorithms for segmenting medical images found in the literature [6].There is a survey of ultrasound image segmentation [7]. Various methods for segmenting ultrasound images have been introduced which are fully automatic [8-12].

A hybrid segmentation method based on morphological operators and on a Gaussian function constraint to delimitate the tumor search dominium both used for tumor segmentation purposes is proposed in [8]. A new automatic seed point selecting method for new region growing algorithm is proposed in [9] for breast lesions. A region based segmentation method for ultrasound images using local statistics is dealt in [10]. This produces results that are less sensitive to the pixel location and it also allows a segmentation of the accurate homogeneous regions. An automatic process to filter, segment and analyze the features of breast nodules in ultrasound images is presented [11]. Anisotropic diffusion filter to suppress speckle noise and radial derivative function to segment the breast lesion in breast ultrasound images is presented in [12]. There are research works which uses watershed segmentation [13-16]. To solve the over

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segmentation problem associated with this method different techniques have been used. There are also research papers on the application of morphological concepts to segment the images [17, 18 and 19]. Only two research papers are found which focus on uterine fibroid segmentation [26, 27]. But these papers work on MRI images. There is no work on ultrasound image with uterine fibroid.

III. PREPROCESSING

The original ultrasound image is preprocessed for removing the speckle noise using morphological image cleaning algorithm. This algorithm works as follows. Initially we define three arbitrary structuring elements with different sizes which resemble the shape of the speckles found in the image. These structuring elements are shown in fig. 1. Using these structuring elements a series of operations such as opening-closing followed by closing-opening is done to remove speckle noise. The top hat and bottom hat of this filtered image is found and they are binarized separately. These two binary images are reconstructed by opening in order to get back the features that were lost while filtering. For reconstructing the features that are lost while cleaning, grayscale opening by reconstruction and grayscale closing by reconstruction are used. These are efficient techniques for getting back the lost image features [1]. Grayscale opening by reconstruction is defined as follows.

Let I and J be two grayscale images defined on the same domain D_I such that I<=J. The grayscale reconstruction by opening of I from J is obtained by iterative grayscale geodesic erosions of J above I until stability is reached.

$$\rho_I(J) = \bigwedge_{n \geq 1} \varepsilon_I^{(n)}(J) \quad (1)$$

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$$\rho_I(J) = \bigvee_{n \geq 1} \varepsilon_I^{(n)}(J) \quad (2)$$

Now the processed top hat is added to the original image and the processed bottom hat is subtracted from it. This procedure is repeated three times with three different predefined arbitrary structuring elements. Now the input image I which is free from speckle noise and which has not lost its features is obtained. It is segmented using the proposed segmentation algorithm.

001100	000000000000	00000000000000
011111	000111100000	00001111000000
000000	011111111110	00111111110000
	011111111100	00111111111110
		01111111111110
		01111111111110

Figure 1. Arbitrary structuring elements a1, a2 and a3

IV. THE PREPROCESSING ALGORITHM

Step 1. Let i=0

Step 2. Let i=i+1

Step 3. Let X=OCCO (I, a_i) where I is the original image with noise and a_i be the arbitrary structure element.

Step 4. Let T(x, y) =tophat (I, X)

Step 5. Find t(x, y) by thresholding T(x, y) using the standard deviation of T(x, y)

Step 6. Let tcap= reconstruction by closing of t

Step 7. Let B(x, y) =bothat (I, X)

Step 8. Find b(x, y) by thresholding B(x, y) using the standard deviation of B(x, y)

Step 9. Let bcap= reconstruction by opening of b.

Step 10. Modify I as X+tcap-bcap

Step 11. Go to step 2 if i<=3.

V. DESCRIPTION OF THE PROPOSED SEGMENTATION ALGORITHM

This algorithm uses mathematical morphological concepts. A binary image is obtained by applying the threshold t on the input image I. This is used to reduce the number of regional minima in the image and also to highlight the fibroid in the image. A regional minimum is a connected component of pixels with the same intensity values i, surrounded by pixels that all have a value greater than i. The input image has many regional minima. This image should be made to have regional minima only as in the binary image. By applying the sup-reconstruction of input image from the binary image, the natural minima catchments from the input image which are not on the binary image are closed. This transformation is called minima imposition. The regional minima in the obtained grayscale image are having intensity value of zero. A marker image is produced from the above image which has extracted only the regions with intensity value zero. The marker image has these extracted regions alone in white color. One of these regions is the small fragment of fibroid. The entire fibroid is not shown as the regional minimum. Only a portion of fibroid is shown. In fact a fibroid is a well circumscribed structure. Hence the entire fibroid structure has to be extracted. The regions touching the border of the image are cleared. The image is divided into 4 blocks namely center-block, left-to-center block, right-to center-block and above-center-block. Each of these blocks is checked to see whether any region is found. One of these blocks will have a region if fibroid is present. The fibroid region alone is kept in the image and the other regions are deleted. The feature called major axis length is extracted from the region and it is used to get the radius of the fibroid. Centroid (xc, yc) which is another feature of the region is extracted. According to the extracted orientation of the region the center of the fibroid is calculated. Using (xc, yc) and calculated radius a circular boundary is defined within which the fibroid lies. Plot the pixels which are similar inside the circular boundary and this result is the segmented fibroid. The contour of the fibroid is extracted from this segmented object.

VI. THE PROPOSED SEGMENTATION ALGORITHM

The cleaned ultrasound image which is free from speckle noise is now used as the input for segmenting.

Step 1. We find the mean m of the pixel values found in the image. We calculate a threshold t as m/2+c where c is a constant. The input image is binarized by applying the threshold t.

Step 2. The resulting binary image from step 1 is imposed on the input image of the algorithm. This is to eliminate all the regional minima except that are available in the binary image.

Step 3. Now a marker image is found from the resulting image of step 2 which identifies the regional minima which are having pixel value 0.

Step 4. Find the block that has the region among the four blocks of the image namely center-block, left-to-center block, right-to center-block and above-center-block.

Step 5. Find the centroid of the region (xc, yc) and calculate the radius of the fibroid using the feature called major-axis-length.

Step 6. If the orientation of the region is vertical and if it is on the right hand side of the fibroid then compute the coordinates of the centre of the fibroid as xf = xc - radius and yf = yc. If the orientation of the region and on the left hand side of the fibroid, calculate xf and yf as xc + radius and yc respectively.

Step 7. If the orientation of the region is horizontal and if it surrounds a hole, modify radius as one third of the previous radius. Find the coordinates of the centre of the fibroid as yf = y coordinate of the top extreme of the region + radius and xf = x coordinate of the midpoint between the x coordinates of the left extreme and right extreme of the region.

Step 8. If the orientation is horizontal and if it is on the lower part of the fibroid, calculate yf =yc - radius and xf = xc.

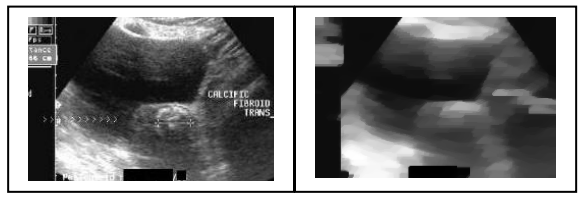
Step 9. Otherwise calculate yf=yc + radius and xf = xc.

Step 10. Define a circular boundary using the centre (xf, yf) and calculated radius.

Step 11. Mark the pixels which are similar inside the boundary.

Step 12. Extract the contour.

Fig. 2 shows an image before and after preprocessing .The sample original images and the results after segmentation algorithm are shown in fig. 3 and fig. 4.



a b

Figure 2. a) Image before preprocessing b) Image after preprocessing

VII. EVALUATION CRITERIA

There are two types of methods for image segmentation evaluation. Analytical methods analyze and evaluate segmentation algorithms themselves by their principles and properties. Empirical evaluation methods, measure the quality of segmentation results. Because empirical evaluation methods provide easy-to-interpret objective evaluations, only empirical methods are commonly used. Ideally, a segmentation result obtained from the algorithm would be compared with an expected segmentation, known as the ground truth. The manual segmentations or ground truths are got from experts, often called as gold standard.

The contour obtained from the segmentation algorithm is usually different from the contour given by the expert. Every pixel in the output of the segmentation algorithm therefore belongs to one of the following classes: True Positive (TP), True Negative (TN), False Positive (FP), or False Negative (FN). These are the evaluation criteria to evaluate the performance of each algorithm. These terms are defined as follows.

TP: A recognized region that is correctly determined to be an object

FP: A recognized region that is incorrectly determined to be an object

TN: An unrecognized region that is correctly determined to be not an object

FN: An unrecognized region that is incorrectly determined to be not an object

The following evaluation measures have also been used to evaluate the performance of the proposed algorithm.

A. Pixel Accuracy

It is defined as (TP+TN)/ (TP+TN+FP+FN) * 100%. It measures the ratio between the pixels/regions which are correctly identified to the total number of pixels/regions.

B. Specificity

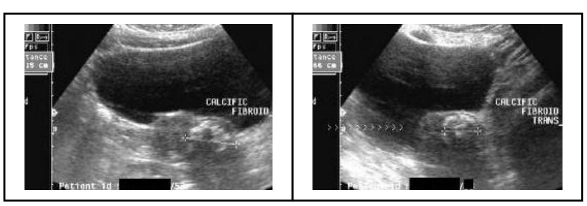
It is defined as TN / (TN + FP) * 100%. This is the true negative rate. It measures the accuracy of a segmenting method to identify all unmarked pixels/regions

C. Sensitivity

It is defined as TP/ (TP+FN) * 100% and is also known as Recall. This is the true positive rate. It measures the accuracy of a segmenting method to identify all marked pixels/regions.

VIII. RESULTS AND DISCUSSIONS

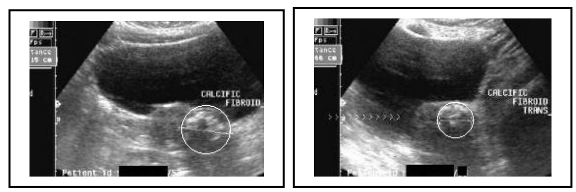
The proposed algorithm is applied on many uterus images found having fibroid on the inner wall of the uterus. The algorithm works well on all the images and gives good results when c is set to 120. The result of this algorithm on three different images is shown in this paper as sample outputs in Fig. 4. The original images are shown in Fig. 3. The performance of the algorithm is measured by the evaluation criteria such as TP, TN, FP, FN, Accuracy, Sensitivity and Specificity. They are tabulated in Table I and II and graphically represented in Fig. 5 and Fig. 6 for 10 images. The performance of the algorithm is very good as the average Accuracy, average Sensitivity and the average Specificity are above 95%. Table I and Table II display the results of performance evaluation of the proposed algorithm.



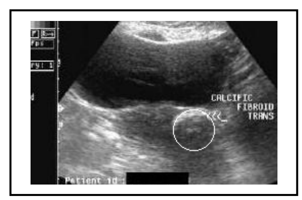
a b

c

Figure 3. Original images before segmentation



a b



c

Figure 4. Result of segmentation algorithm

TABLE I. EVALUATION MEASURES TP, TN, FP, FN

Image	TP	TN	FP	FN
Image1	1349	37068	87	297
Image2	1451	36836	417	97
Image3	2451	35277	789	284
Image4	1291	37175	70	104
Image5	1852	36387	253	309
Image6	3460	34394	760	187
Image7	2220	35959	182	279
Image8	1347	37038	151	104
Image9	1192	37199	169	80
Image10	3536	34527	684	54

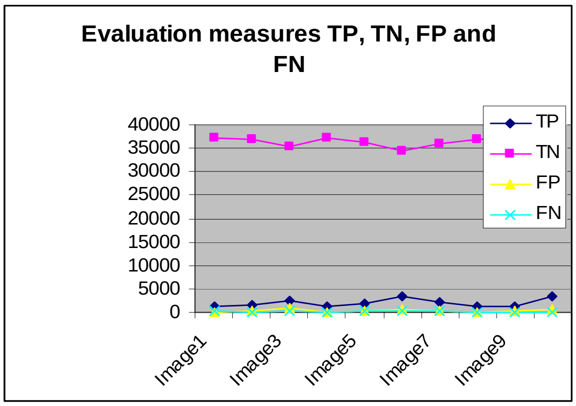


Figure 5. Graphical representation of TP, TN, FP and FN

TABLE II. EVALUATION MEASURES ACCURACY, SENSITIVITY & SPECIFICITY

Image	Accuracy	Sensitivity	Specificity
Image1	99.010335	81.956258	99.765846
Image2	98.675292	93.733850	98.880627
Image3	97.234607	89.616088	97.812344
Image4	99.549689	92.544803	99.812055
Image5	98.551584	85.701064	99.309498
Image6	97.559341	94.872498	97.838084
Image7	98.806936	88.835534	99.496417
Image8	99.340062	92.832529	99.593966
Image9	99.355590	93.710692	99.547741
Image10	98.097987	98.495822	98.057425
Average	98.618142	91.229914	99.011400

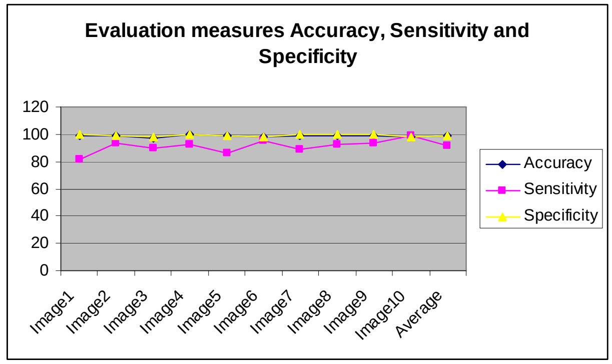


Figure 6. Graphical representation of Accuracy, Sensitivity and Specificity

IX. CONCLUSION

The subjective appearance of the output image is good. Performance of this algorithm is also very good. It takes less time and storage. It is fully automatic as it does not require human intervention. It is fast as compared to segmentation procedures like level set methods. There is no need to give the seed point to start segmentation

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