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An Efficient Method for Hepatic Cyst Segmentation on Ultrasound Images

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ABSTRACT

Hepatic cysts are usually rare complications but when they occur they may be fatal. Thus the radiologist should be able to monitor the cyst regularly and for doing so they need some parameters to monitor. The size of the cyst being one of the parameters that can be monitored after the segmentation of the cysts. The present work is focused on the designing of a modified method that can segment hepatic cyst on ultrasound images. This proposed method is designed by modification in geometric method proposed by Chan and Vese [1] which is combination of active contour and level set method. The work is performed on seventeen clinically acquired ultrasound images, which comprises of 6 small, 5 large, 4 multiple and 2 atypical type cyst images. The modified method is validated by both qualitative and quantitative criteria. The performance of proposed method can be expressed in terms of accuracy, sensitivity and specificity showing 97.9%, 77.3% and 90.7% for small cysts, 94.1%, 68.0% and 80.0% for large cysts, 98.2%, 96.3% and 98.5%for multiple cysts and for 95.7%, 68.9% and 91.3% atypical cysts respectively. The results demonstrate that the modified method can segment effectively hepatic cyst on ultrasound images and therefore can be used by the radiologist for diagnostic purposes.

Keywords: Hepatic cyst, Image processing, Image segmentation, Ultrasound images, Active contour.

1 Introduction

Hepatic cysts are abnormal, fluid-filled bubble like-structures that may develop in the liver approximately from 2% to 7% of the population [2-3]. Not more than 10-15% of these patients have symptoms that bring the cyst to the clinical attention [4]. Even though most liver cysts are benign, an early diagnosis is critical for proper treatment of the parasitic or cancerous subtypes. The radiologist must be able to recognize the key imaging features like location of the cyst, its size, the presence and thickness of a wall or any internal septations or mural nodules, and the pattern of enhancement following intravenous contrast that will enable them to diagnose the rare complications associated with it [5].The size of the cyst being one of the key features can be monitored by any imaging modalities like ultrasound, computerized tomography or magnetic resonance imaging to monitor the size of the cyst. Ultrasound is a preferred imaging modality for the diagnosis and identification of the cyst with its typical characteristic appearance of bright walls and dark centers on ultrasound images as shown in Figure1 [6].

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As ultrasound uses non-ionizing radiation, physicians consider it to be minimally-invasive and safe. It is portable and cost effective method for analyzing cyst in its initial phase.

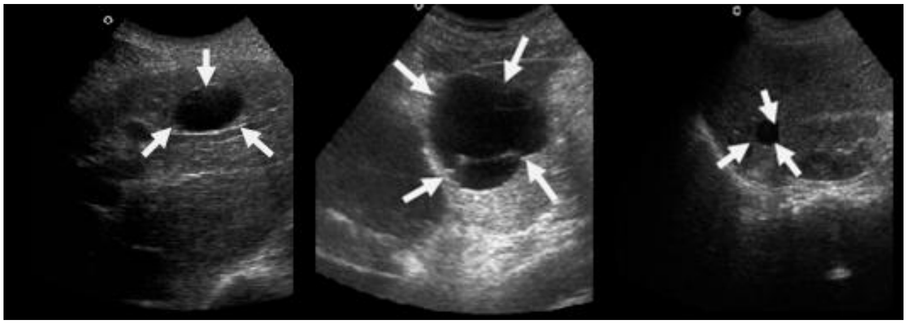

Figure 1 Typical characteristics of hepatic cyst on ultrasound images

Segmentation of ultrasound images is a very well known challenging problem. It may be the one of the reasons that very few research works have been done in this direction till date. The challenges with images arise because of characteristics artifacts attenuation, speckle, shadows, and signal dropout. The research works that have been done to develop effective methods for segmentation on ultrasound images are summarized in Table 1.

Active contours, or snakes, are curves that are defined within an image and can move under the influence of internal forces coming from the curve itself and external forces computed from the image data. The essential idea is to evolve a curve or a surface under constraints from image forces so that it is attracted towards hepatic cyst on ultrasound image. Snakes are widely used in many applications, including edge detection, shape modeling, segmentation, and motion tracking. The active contour models in literature can be classified into two broad categories: parametric active contours [5, 6] and geometric active contours [7-9]. In parametric type active contour, a parameterized curve is used and energy-minimizing is done to move the curve. This active contour method has two major disadvantages:

i. The minimization function depends on the parameters of the curve, as the parameters change the minimization function changes and effects the segmentation.

ii. The parameterized active contour cannot handle changes in the topology. Thus it cannot be used for detection of multiple cysts as it cannot merge or split easily.

To overcome these disadvantages, geometric type active contour method was introduced in which level set method is used to initialize the curve. The level set formulation works on the bases that a curve can be seen as the zero level set of a function in higher dimension. Level set methods provide an efficient and stable algorithm to solve curve evolution equations. This method has many advantages over parametric type active contour method. The advantages are:

i. The changes in topology of the active contour are handled easily during the curve evolution.
ii. For numerical approximations, a simpler method like fixed discrete grid in the spatial domain and finite-difference approximations for spatial and temporal derivatives can be used.
iii. Level set method used for initialization of the curve can be extended to any dimension which is not that simple in parametric type of active contour.

Table 1 Literature review summary

Authors [Ref.]	Year	Database images	Method	Pros	Cons
Davignon et.al [8]	2005	1000	• Ashton and Parker algorithm.	• The segmentation results are improved by increasing the number of features used.	• The segmentation cannot be done effectively if the initial location of the region is not given.
Zhu et.al [9]	2010	20	• Gradient Vector Flow active contour method.	• The method is insensitive to noise and clutter. • It improves the problem of weak-edge-leakage in many cases.	• Cannot be used for detection of multiple lesions as it uses parametric type active contour method.
Huang et. al [10]	2011	20	• Graph-based method	• efficiency of the Snake improved by the hybrid segmentation • The accuracy is improved by 1.5 – 5.6% from the previous methods.	• Size of the sample effects the segmentation results as the parameter calculation takes time in semi-automatic method.
Singh et.al [11]	2013	180	• Texture analysis	• sensitivity is 100% • high accuracy	• Do not classify data into sub categories
Feng et.al [12]	2013	294	• Novel approach	• extremely fast level set based structure segmentation algorithm	• accuracy varies upon the quality of the image used
Zhu et.al [13]	2016	92	• Weller's adaptive threshold • Particle swarm optimization (PSO)	• Performs precise segmentation and identification in less than a minute.	• Noise reduction should be performed in preprocessing.
Jain et.al [14]	2016	37	• Iterative Fuzzy C-Mean Method	• The segmentation is done within 14.25 s	• Database used is less

2 Materials and Methods

2.1 Materials

Ultrasound image database used in this research work has been acquired from the Department of Radio diagnosis, Postgraduate Institute of Medical Education & Research (PGIMER), Chandigarh, India. The database contains 17 clinically acquired B-1 mode ultrasound images of hepatic lesions. The images are characterized according to the type, numbers and size. This categorization is clearly depicted in Figure2

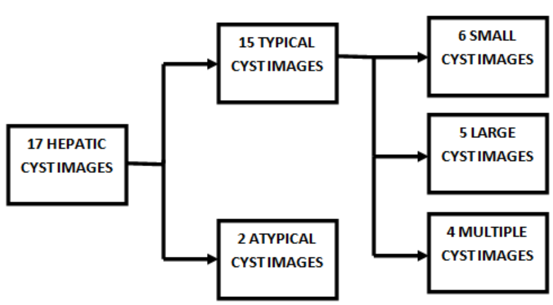

Figure 2 Flowchart giving the database description

2.2 Method

The proposed method uses geometric active contour to detect hepatic cyst in a given ultrasound image as shown in Figure 3. The segmentation is done by minimizing an energy function, for this method Mumford- shah segmentation functional is used. Let us assume that there is an image I, region showing hepatic cyst will be characterized by different intensity values and the other parts of the image with different intensity values. Let B_0 be the boundary of the cyst and C be the variable curve. By calculating the average intensity inside C and outside C respectively, the fitting terms F_{in} and F_{out} are calculated.

$$F(C) = F_{in} + F_{out} \tag{1}$$

$$F(C) = \int_{inside(C)} |I(x,y) - c1|^2 + \int_{outside(C)} |I(x,y) - c2|^2 \tag{2}$$

Discretizing this energy function and writing it as a pixelwise function gives:

$$F(x,y) = |I(x,y) - c1|^2 - |I(x,y) - c2|^2 \tag{3}$$

Where C is any other variable curve, and the constants c1 and c2 depending on C, are the average intensity of inside and outside the curve respectively .If the curve is outside the cyst, $F_{in} > 0$, and F_{out} almost becomes zero. If the curve is inside the cyst, $F_{out} > 0$, and F_{in} almost becomes zero. The fitting energy will be minimized only when curve C will be at B_0. The step wise description of the method is given below:

Step 1: Remove the patients basic information like name, age, gender, etc. from the image as per the ethical regulation and read the input image, *I*.

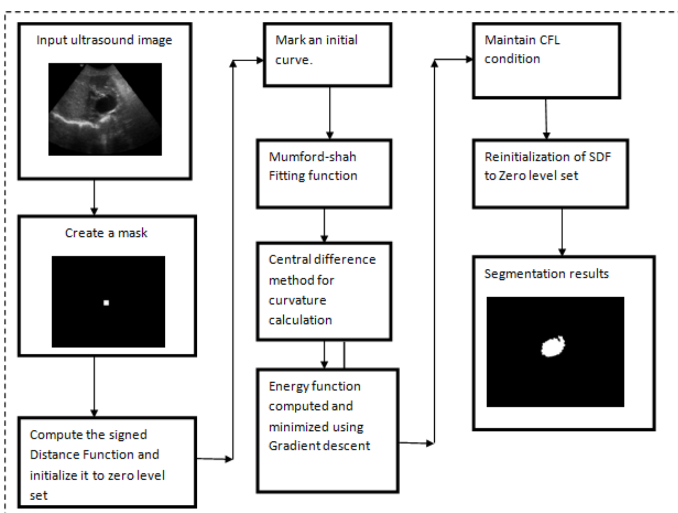

Figure 3 Flowchart describing the methodology

Step 2: Create a binary mask*, m* location and size of the white part of the mask depends upon the location and size of the cyst on an ultrasound image.

Step 3: The size of the image as well as the mask is reduced by 50% to decrease the computation time.

Step 4: Signed distance function (SDF), *phi* of the mask is computed using the Euclidean distance and is initialized to zero level set. Using *phi*, the initial contour is marked.

Step 5: The points that lie inside the initial contour are found and their mean value, U is calculated. Similarly the points that lie outside the initial contour are found and their mean value, V is calculated.

Step 6: Using the mean values, the internal, F_{in} and external F_{out} fitting terms are calculated and thus the total Mumford-shah fitting term is formulated as defined in (3).

Step 7: The curvature of the curve is calculated using the central difference method and is given by the formula

$$curvature = \frac{F_X F_{YY} - F_Y F_{XX}}{(F_X F_X + F_Y F_Y)} \tag{4}$$

Step 8: When we multiply curvature of the curve with the normalized value of Mumford-shah fitting term, we get the overall energy, *E* which is minimized using the descent gradient method.

Step 9: The minimization involves convergence of finite differences for which Courant-Friedichs-Lewy (CFL) condition is maintained.

Step 10: The signed distance function of the curve is reinitialized to its zero level set using sussman method again and again to prevent the level set function to become too flat.

Step 11: The evolution of the curve will stop once the energy function is minimized. The minimum value of the energy function will be obtained at the boundary of the cyst.

2.2.1 Original Method:

In this method central difference was calculated using three points. F_X, F_Y is the first order central difference in X and Y direction respectively, F_{XX} and F_{YY} are the second order central difference in the X and Y direction.

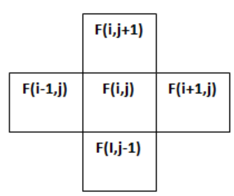

Figure 4 Three point template

$$F_X = \frac{F_{(i+1,j)} - F_{(i,j)}}{2\Delta X} \tag{5}$$

$$F_Y = \frac{F_{(i,j+1)} - F_{(i,j)}}{2\Delta Y} \tag{6}$$

$$F_{XX} = \frac{F_{(i-1,j)} - 2*F_{(i,j)} + F_{(i+1,j)}}{(\Delta X)^2} \tag{7}$$

$$F_{YY} = \frac{F_{(i,j-1)} - 2*F_{(i,j)} + F_{(i,j+1)}}{(\Delta Y)^2} \tag{8}$$

2.2.2 Modified Method:

In the original method, they have used 3 points to calculate the central difference, But as more number of points are used to calculate the centre difference for more accurate result.

(1) Central difference using 5 points

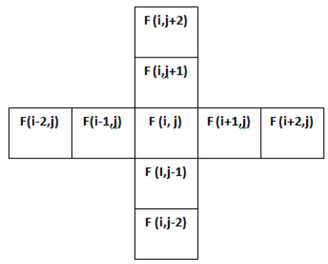

Figure 5 Five point template

$$F_X = \frac{F_{(i-2,j)} - 8*F_{(i-1,j)} + 8*F_{(i+1,j)} - F_{(i+2,j)}}{12\Delta X} \tag{9}$$

$$F_Y = \frac{F_{(i,j-2)} - 8*F_{(i,j-1)} + 8*F_{(i,j+1)} - F_{(i,j+2)}}{12\Delta Y} \tag{10}$$

$$F_{XX} = \frac{-F_{(i-2,j)} + 16*F_{(i-1,j)} - 30*F_{(i,j)} + 16*F_{(i+1,j)} - F_{(i+2,j)}}{12*(\Delta X)^2} \tag{11}$$

$$F_{YY} = \frac{-F_{(i,j-2)} + 16*F_{(i,j-1)} - 30*F_{(i,j)} + 16*F_{(i,j+1)} - F_{(i,j+1)}}{12*(\Delta Y)^2} \tag{12}$$

Where ΔX and ΔY is the unit change in X and Y direction respectively.

(2) Central difference using 7 points:

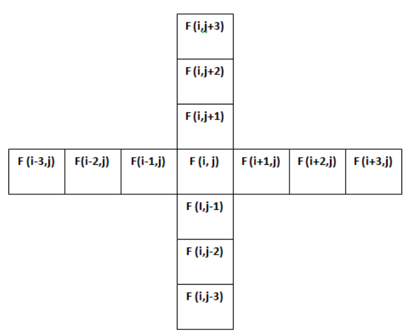

Figure6 Seven point template

$$F_X = \frac{-F_{(i-3,j)} + 9*F_{(i-2,j)} - 45*F_{(i-1,j)} + 45*F_{(i+1,j)} - 9*F_{(i+2,j)} + F_{(i+3,j)}}{60*\Delta X} \tag{13}$$

$$F_Y = \frac{-F_{(i,j-3)} + 9*F_{(i,j-2)} - 45*F_{(i,j-1)} + 45*F_{(i,j+1)} - 9*F_{(i,j+2)} + F_{(i,j+3)}}{60*\Delta Y} \tag{14}$$

$$F_{XX} = \frac{2*F_{(i-3,j)} - 27*F_{(i-2,j)} + 270*F_{(i-1,j)} - 409*F_{(i,j)} + 270*F_{(i+1,j)} - 27*F_{(i+2,j)} + 2*F_{(i+3,j)}}{180*(\Delta X)^2} \tag{15}$$

$$F_{YY} = \frac{2*F_{(i,j-3)} - 27*F_{(i,j-2)} + 270*F_{(i,j-1)} - 409*F_{(i,j)} + 270*F_{(i,j+1)} - 27*F_{(i,j+2)} + 2*F_{(i,j+3)}}{180*(\Delta X)^2} \quad (16)$$

2.2.3 Statistical parameters

Performance of the proposed method is evaluated by the medically important statistical parameters. These parameters are described below:

The term TPP represents total number of pixels of the cyst that are correctly classified, TNP is the total number of pixels of the background that are correctly classified, FPP is the total number of pixels of the region segmented by the method which are not in reality the part of the cyst, FNP are the total number of pixels which are not in the segmented region but which in reality are the part of the cyst.

Sensitivity: is the measure of probability by which a method can detect to a hepatic cyst pixel correctly among total number of hepatic cyst pixels.

$$Sensitivity = \frac{TPP}{TPP+FNP} * 100\% \quad (17)$$

Accuracy: it demonstrates the extent of the correctly detected cystic and non cystic pixels got by the test technique out of all pixels of the physically portrayed area.

$$Accuracy = \frac{(TPP+TNP)}{(TPP+TNP+FNP+FPP)} * 100\% \quad (18)$$

Specificity: is the measure of probability of detecting correctly the background pixels among actual number of background pixels present in the image.

$$Specificity = \frac{TNP}{TNP+FPP} * 100\% \quad (19)$$

3 Results and Discussions

The original [1] and the modified methods are tested on 17 ultrasound images of hepatic cyst. Their performance is compared both by the qualitative and quantitative criterion. In Figure 7 we can visualize the comparative results for the three points, five points and seven points central difference method. The qualitative analysis although is not very accurate but we can see that the results of five point central difference method is comparatively better than other two methods. The contour is closer to the boundary of the cyst as compared to the three and seven point method. The improvement can be seen

more clearly in Figure8, Figure9, fig 10 and Figure11.

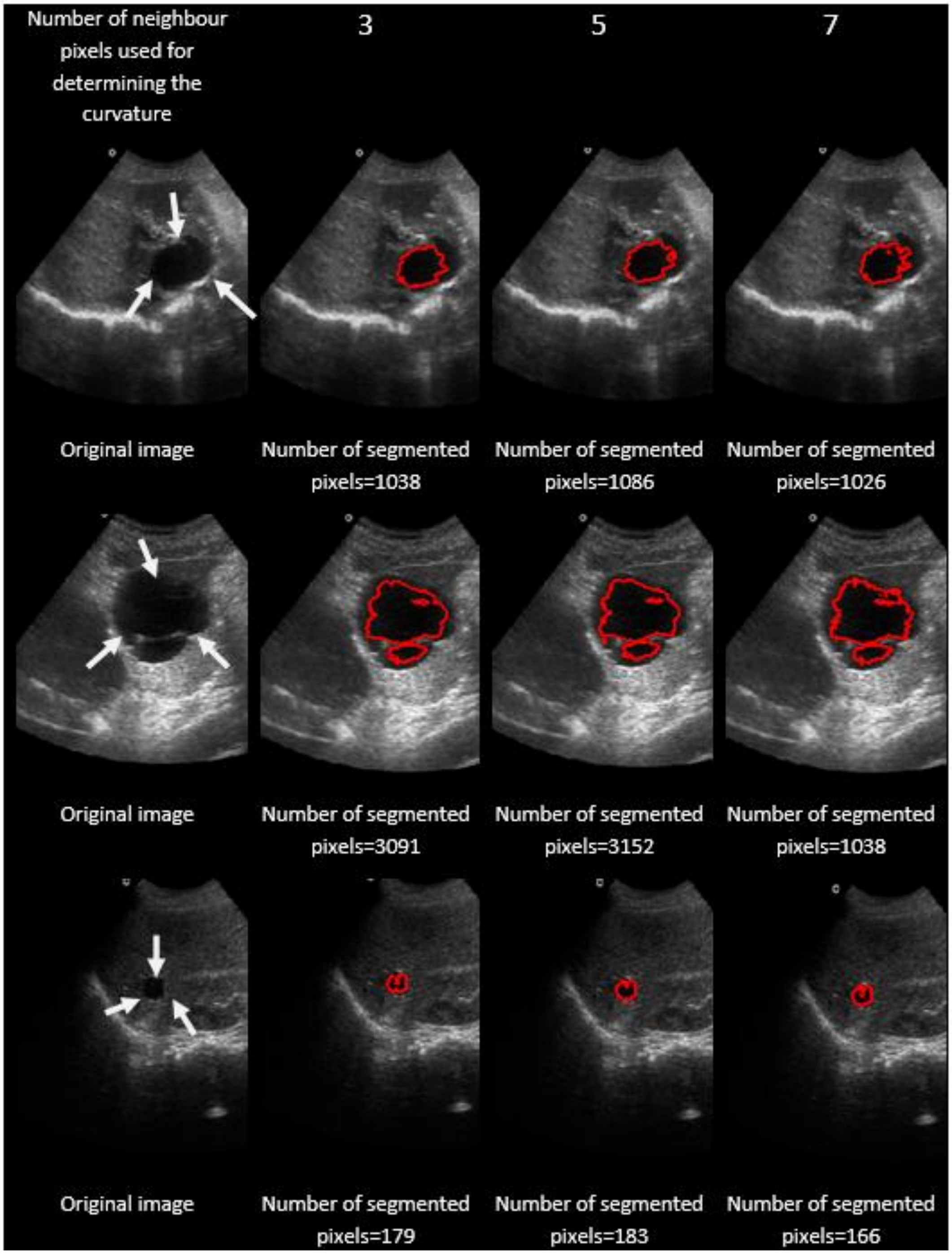

Figure 7 Comparative segmentation results of three, five and seven point central difference method

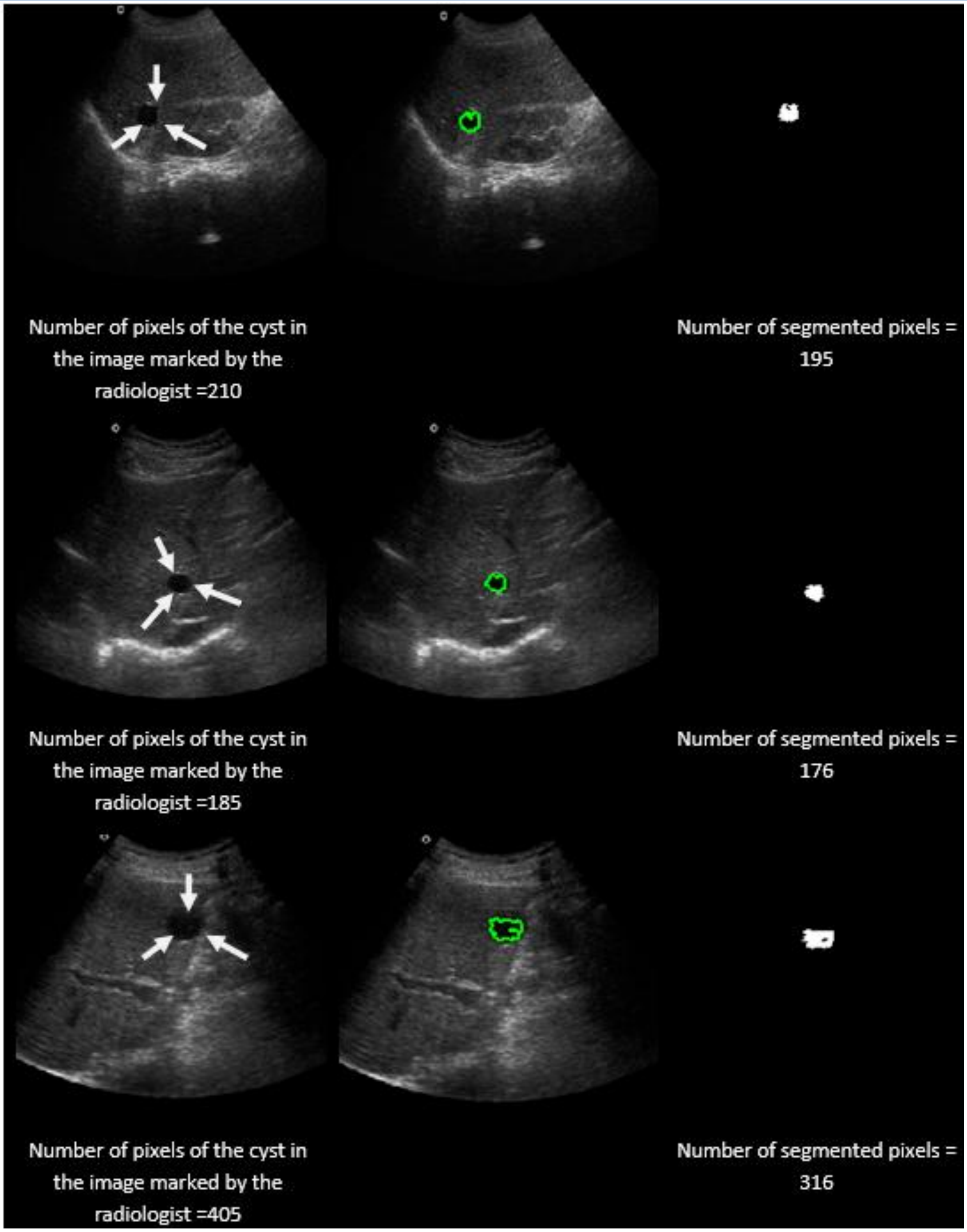

Figure 8 Results of segmentation of small hepatic cyst using 5 point central difference method

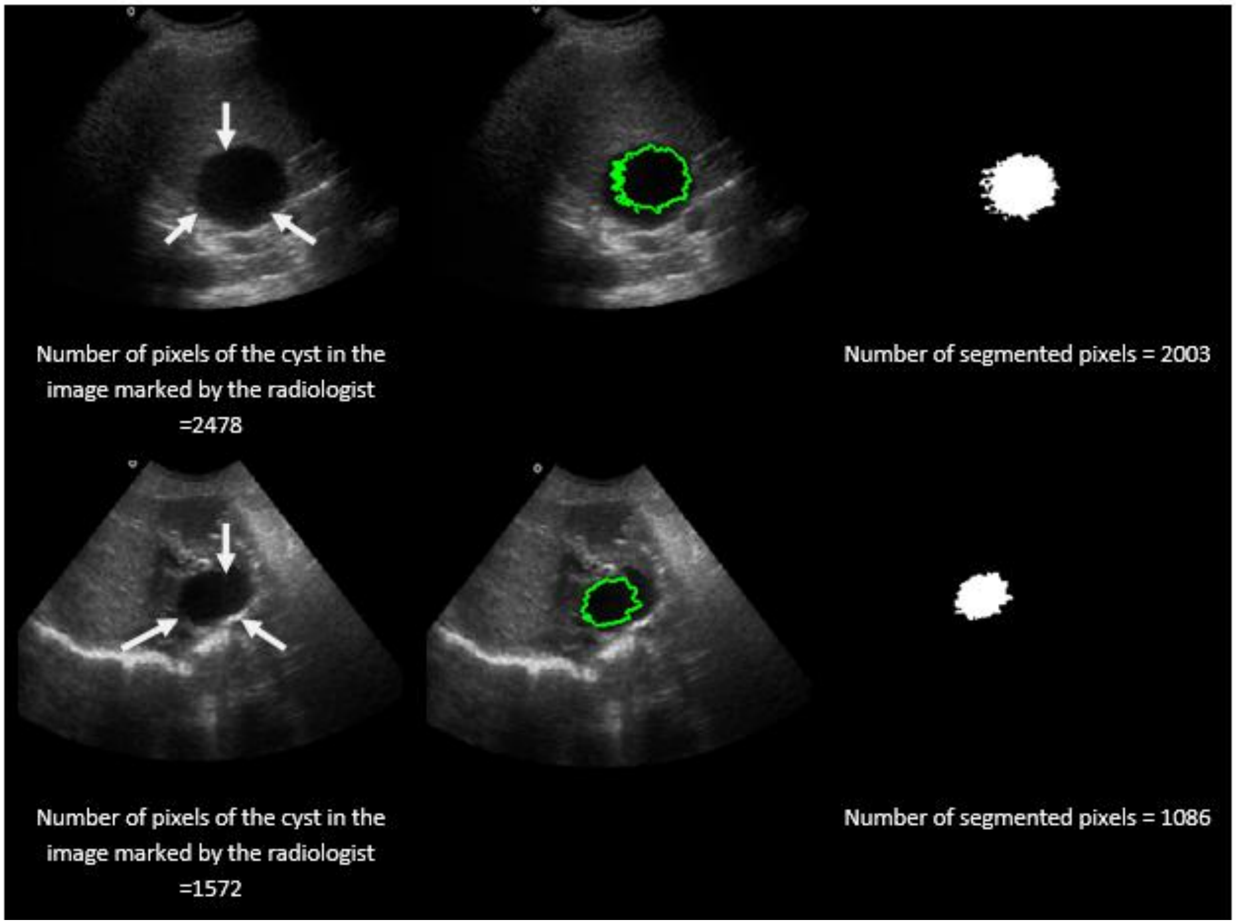

Figure 8 Results of segmentation of large hepatic cyst using 5 point central difference method.

The results obtained from the segmentation method for small cyst is shown in Figure 8. Although from the results the method cannot be validated accurately but still we can visualize that by using five point methods in place of three points for the calculation of the curvature, the contour includes more number of pixels and the value is closer to the value given by the experts. Similarly, the results for large cyst are shown in Figure9, for multiple cysts in Figure10 and that for atypical cyst in Figure11 respectively.

The qualitative analysis is not sufficient for proving the accuracy of the method. Thus it is important to perform the quantitative analysis. The quantitative analysis is performed by using medically important statistical parameters like sensitivity; accuracy and specificity are calculated for both original and the modified method as shown in table 2. As we can see the values are improved and this proves that the modified method is better and has high performance compared to the original method.

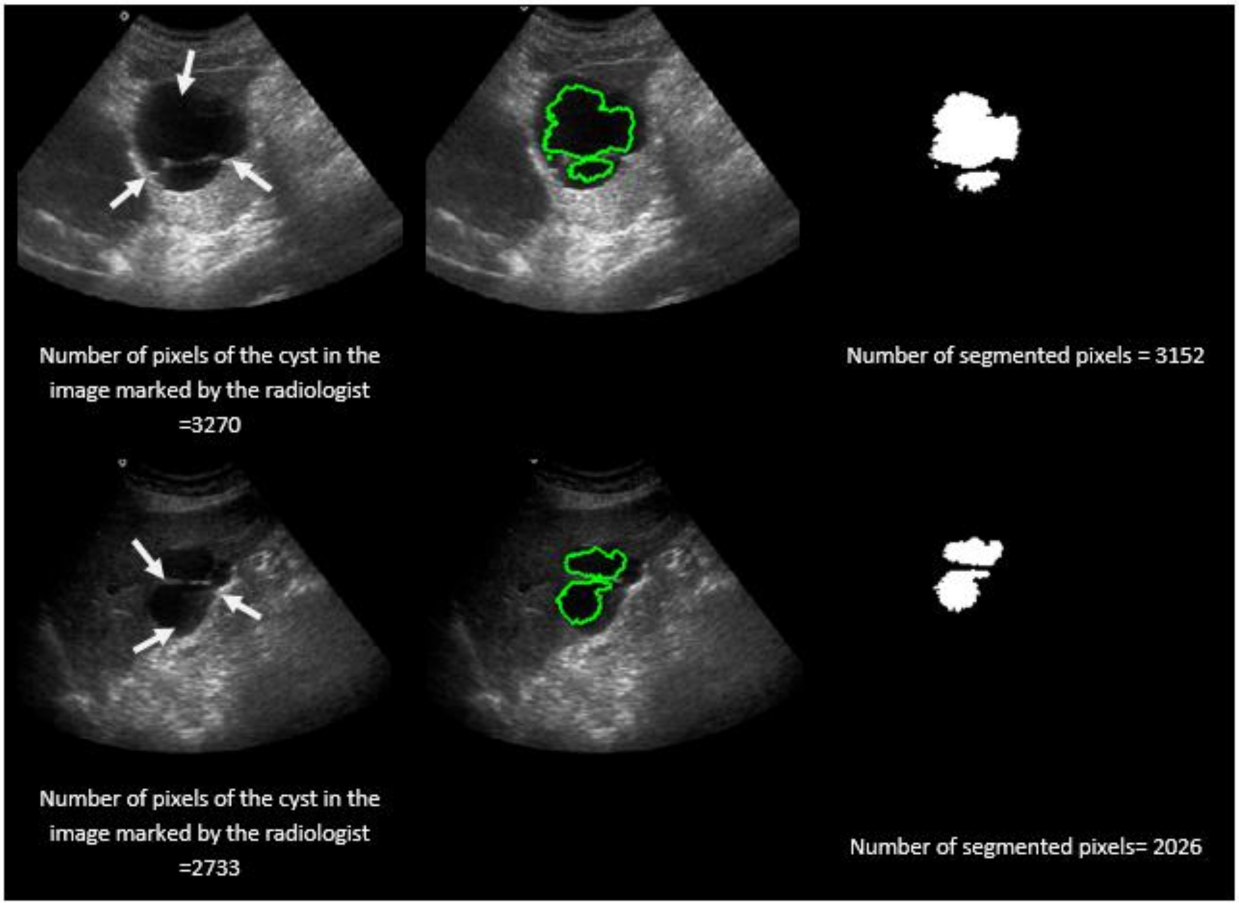

Figure 9 Results of segmentation of multiple hepatic cysts using 5 point central difference method.

Table 2 Comparison of proposed and modified method based on statistical parameters

Parameters		Accuracy (%)		Sensitivity (%)		Specificity (%)	
		Proposed Method	Modified Method	Proposed Method	Modified method	Proposed Method	Modified method
Typical	Small cyst	95.9	97.9	73.0	77.3	88.4	90.7
	Large cyst	93.1	94.1	65.6	68.0	73.2	80.0
	Multi cyst	96.2	98.2	94.5	96.3	94.5	98.5
Atypical		94.9	95.7	66.5	68.9	83.4	91.3

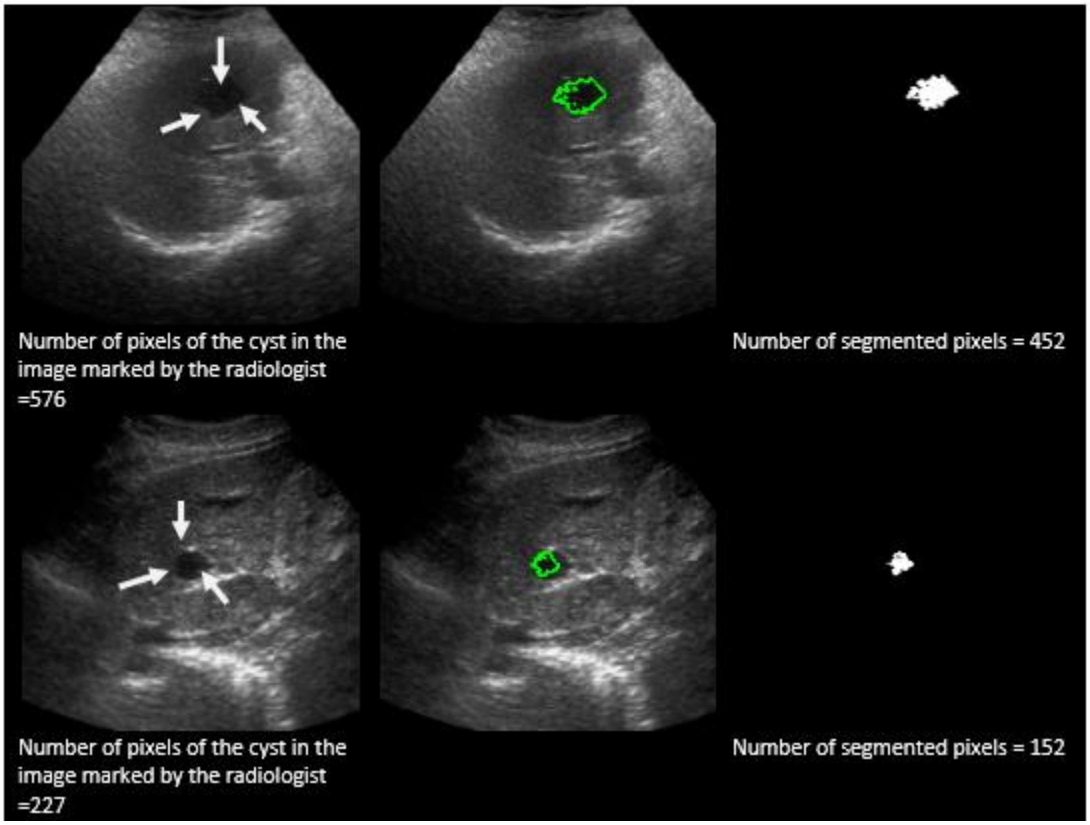

Figure 10 Results of segmentation of atypical hepatic cysts using 5 point central difference method.

4 Conclusion

Active contours, also called snakes, are used extensively in computer vision and image processing applications, particularly to locate object boundaries. There are two types of methods used for active contours parametric method and geometric method. In this paper geometric method is used. The original method is modified by using higher number of points to calculate the central difference and thus the curvature. Thus regions that are not surrounded by definite boundaries can now be segmented more accurately and precisely. The method was tested on 17 images and the results are validated in both quantitative and qualitative manner. For quantitative analysis, statistical parameters like accuracy, specificity, sensitivity are obtained as 97.9%, 77.3%, 90.7% for small cyst, 94.1%, 68.0%, 80.0% for large cyst, 98.2%, 96.3%, 98.5% for multiple cyst and 95.7%, 68.9%, 91.3% for atypical cyst respectively. This method has obtained high accuracy for the segmentation of hepatic cyst on ultrasound images than the original method and thus is very reliable.

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