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Segmentation and Feature Extraction of Ultrasound Images by Modified Level Set Method and Chain-VESE Methods Using SRAD Filter

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Abstract-***Cancer is one of the most dreaded disease for mankind, if tumour are detected at initial stages then this disease can be completely cured, there are so many models in diagnosis of cancer one of these model is diagnosis through Ultrasound Images. So this paper proposes a model to segment the abnormality present in the Ultrasound image such as tumour or the lesion or the calculi. This model can be proposed for diagnosing and segmenting kidney calculi, lesions in ultrasound images. Compared to other methods of diagnosing tumours Ultrasound is more effective and easy to implement, less complicated and less in cost compared to CT scan and other methods. Segmentation of ultrasound images presents a unique challenge because these images contain strong speckle noise. There are many models for segmenting lesions from Ultrasound images but they are specified only to some organs like only to breast cancer or to prostrate cancer or only to the liver images but proposed model can be used to segment all Ultrasound B-mode images. So proposed model is tried on five different sets of Ultrasound images like kidney, liver and uterus to check the robustness of the model. The proposed model first the ultrasound image is developed from an organ then it is applied to SRAD filter to reduce the speckle and retain the edges of the images along with lesion part then we perform Automatic Thresholding is performed by Otsu algorithm followed by initializing Active contours by level set method and at last we segment the lesion by using Chan Vese model. Results are compared with various theoretical threshold values with the experimental values are closely approximated by the mean of zeroth and first order cumulative methods for texture features like area, solidity, perimeter. This method is simple compared to other methods and can be used for any B – mode Ultrasound images.***

Keywords – Ultrasound Images, Fully Automatic Segmentation, Core Area, Adaptive Threshold, Prostrate Segmentation, Breast Lesion

I. INTRODUCTION

Cancer is the most deadly disease in both men and women there are several types of cancer like lung cancer, Prostrate cancer, Breast Cancer, Uterus Cancer etc these diseases can cause of death Hence diagnosis of the cancer in the early stages is crucial. Ultrasound imaging is a widely used technology for diagnosing and treatment of cancer. Non-invasive methods used to diagnose cancer still have limitations. Detection techniques are currently based primarily on physical examination. Ultrasound image segmentation is an important problem in medical image analysis and visualization. Because these images contain strong speckle noise and attenuation artefacts [3], it is difficult to automatically segment these images to detect interested objects in the correct position and orientation. Most image segmentation methods use different approaches like focus on *region growing* or *active contours*. For instance, to segment homogenous regions, the region growing method [3] first requires users to identify a seed point, using geographic priority and a multi-feature vector space of the seed point as criteria. The interference of speckle noise makes it unreliable to classify image pixels. The active contour methods (e.g., [4]) are designed to find edges of a region whose colour or other features are significantly different from those of the surrounding region. However, speckle noise makes clear edges difficult to detect. Furthermore, most active contour-based approaches are developed from the *snake* algorithm, which requires the user to identify an initial contour. Thus, both methods are only semi-automatic systems and suffer from speckle noise, which are present in ultrasound images.

II. Image acquisition

Ultrasound elastography and echography images of breast or liver or kidney are acquired using a transducer. Initially B mode image of the lesion is taken, following which a slight compression is applied. The effect of breathing and heart beat produce the required compression. The elastogram is generated by the machine by comparing pre and post compressed RF signals and the elastogram is displayed adjacent to the B mode image. The ultra-sonograms and elastograms generated are grey scale images.

III. Speckle in Ultrasound Imaging

Speckle in US B-scans is seen as a granular structure which is caused by the constructive and destructive coherent interferences of back scattered echoes from the scatterers that are typically much smaller than the spatial resolution of medical ultrasound system. This phenomenon is common to laser, sonar and synthetic aperture radar imagery (SAR). Speckle pattern is a form of multiplicative

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noise and it depends on the structure of imaged tissue and various imaging parameters.
Speckle degrades the target delectability in B-scan images and reduces the contrast, resolutions which affect the human ability to identify normal and pathological tissue. It also degrades the speed and accuracy of ultrasound image processing tasks such as segmentation and registration. The nature of the speckle pattern can be categorized into one of three classes according to the number of scatters per resolution cell or the so called scatterer number density (SND), spatial distribution and the characteristics of the imaging system itself.

IV. Segmenting the lesion

Due to noise and speckles in the ultrasound B mode and electrographic images, noise filtering and edge-enhancement are required. There are several fundamental requirements of noise filtering methods for medical images. One, it should not lose the important information of object boundaries and detailed structures. Two, it should efficiently remove noise in the homogeneous regions and finally, it should enhance morphological definition by sharpening discontinuities. The Speckle Reducing Anisotropic Diffusion (SRAD) filter (Yongjian Yu and T. Scott Acton, 2002) meets these requirements of noise filters and also improves the image quality significantly while preserving the important boundary information and hence, in present study, speckle reducing anisotropic diffusion filtering of real elastography and ultrasound B mode images is done to reduce noise and speckles. Segmentation is required to separate the tumour region from its background. Segmentation algorithms for grey scale images are based on one of the two basic properties of image intensity values: discontinuity and similarity. In the first category, the approach is to Partition the image based on abrupt changes in the intensity, such as edges in an image. The principal approaches in the second category are based on partitioning an image into two regions that are similar according to a set of predefined criteria. In present study, automatic threshold and level set active contour method, based on the above criteria are used for segmentation. An automatic threshold-determination method, proposed by Otsu (1997), can choose the threshold to minimize the intra class variance of the black and white pixels automatically. An additional control scheme is allowed to enable the user to change the threshold value when he is not satisfied with the threshold value assigned by this automatic method. In an elastogram, the tumour region appears to be darker and the background bright. In present study, the pre-processed images are subjected to the above mentioned automatic threshold scheme, resulting in binary images as this aids in separating the lesion from its background. The area of lesion is segmented from the binary image by applying level set segmentation technique.

V. Level set method

Level sets are first described by Osher and Sethian (1988) as a method for capturing moving fronts. In the level set formulation, the segmentation problem is equivalent to the computation of a surface Γ (t) that propagates in time along its normal direction. The Γ surface is also called a propagating front, which, according to Osher and Sethian (1988), is embedded as a zero level of a time varying higher dimensional function

$$f(x, t):\ \Gamma(t) = \{ x \in R^3 \mid \varnothing (x, t) = 0 \}$$

An evolution equation for an interface Γ, where Γ is a closed curve in Â2, can be written in a general form. The function f describes a curve defined by:

$$f(x, t) = d$$

Where, d is a signed distance between x and the surface Γ. If x is inside (resp. outside) of Γ, then d is negative (resp. positive). The function F is a scalar speed function that depends on image data and the function f. The main drawback of this procedure is that during the evolution, f can assume sharp or flat shapes. To overcome this problem, f is initialized as a signed distance function before the evolution. Later, during the evolution, it is periodically reshaped to be a signed distance function (Li *et al*., 2005). Li *et al*. (2005) proposed a modification of traditional variational level sets to overcome the problem of the reshaping of function f to be a distance function within the evolution cycle.

In present study, variational level sets are used, which are more robust than those originally proposed by Osher and Sethian because they incorporate shape and region information into the level set energy functions. Here, the initial contours of lesions of both ultrasound and elastography images are determined by the method proposed by Xia and Liu (2007). This
Algorithm consists of finding all endpoints in an edge map. All the valid pairs are established. The linking cost for all the valid pairs is computed. All the pairs keyed on cost are placed in a heap with the minimum cost pair at the top. The pair of least cost from the heap is iteratively linked and the connected pair is removed. This algorithm has been applied to both ultrasound B mode and elastography images. After tumor contours are segmented from the elastographic and US B mode images, six texture features, three values for features of strain-contour difference, perimeter difference and area difference and two values for the shape feature- solidity and width to height difference are computed.

VI. Segmentation

We have described briefly about segmentation in chapter 1 i.e in the Introduction so in this unit we discuss segmenting of Active contour by Chan – Vese Model

1). Introduction to Chan-Vese Model

In Chan and Vese proposed an active contour model using an energy minimization technique. Their model works on noisy and blurred images, and does not rely on gradient values to find the boundary. Assume that *I* is given image. The curve is represented implicitly via a Lipschitz function φ , by $C = \{(x, y) \mid \varphi (x, y) = 0\}$, and the evolution of the curve is given by the zero-level curve at time of the

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function φ (*t*, *x*, *y*) . Chan and Vese deduced the associated Euler-Lagrange equation for φ on the base of Mumford-Shah functional

$$C_1(\emptyset) = \frac{\int IH(\emptyset)dx}{\int H(\emptyset)dx},\ c_2(\emptyset) = \frac{\int I(1-H(\emptyset))dx}{\int (1-H(\emptyset)dx}$$

$$\frac{\partial \emptyset}{\partial t} = \delta(\emptyset)[\mu \nabla . \frac{\nabla \emptyset}{|\nabla \emptyset|} - v - \lambda_1(I - c_1)^2 + \lambda_2 (I - c_2)^2$$

$$\emptyset(0, x) = \emptyset_0(x)$$

Where $\mu \geq = 0$, $v \geq 0$, $\lambda_1, \lambda_2 > 0$are fixed parameters,

H (z) = { 1, z $\geq$ 0} { 0 , z $<$ 0 is Heaviside function and δ (z) = $\frac{d}{dz}$ H(z) is diarc function. Using the δ (z) = ε / ($\pi(\varepsilon^2 + z^2)$),)) , Chan- Vese model can automatically detect interior contours. But since this model has the tendency to seek local minima, it will behave unsatisfactorily when the image domain encompassed by interior contour is small and far away from initial contour

VII. RESULTS

1). Feature extraction:

Features are to be computed from the segmented region to identify lesions for different thresholds. In the next section we are going to compare area difference, perimeter and solidity for different threshold for five sets of images and compare with the threshold got by the mean of zeroth and first order thresholds.

2). Area difference:

The area difference is used to compare areas of lesions between two images, as lesion area changes in accordance to the applied pressure. The area difference is defined as the difference between areas of lesions in the ultrasound images and elastograms divided by the number of pixels in the lesion region of the ultrasound image:

$$\text{Area difference} = \frac{i-j}{i} * 100$$

where, 'i' and 'j' the lesion areas of ultra-sonogram respectively.

3). Perimeter difference:

The perimeter of the lesion is computed by calculating the distance between each adjoining pair of pixels around the border of the region. It is length of the nuclear envelope calculated as the length of a polygonal approximation of the boundary (B), where p is perimeter of lesion. Polygonal approximation is approximating a closed curve as a 2D polygon by which a simple representation of the planar object boundary is provided:

$$P = \sum_{x \in B} 1$$

The perimeters of lesions in ultra-sonogram computed.

4). Solidity:

Shape values can be used to distinguish between benign and malignant tumors. Benign lesions usually have smooth shapes and so they produce a regular shape in both ultrasound and elastographic images whereas malignant lesions present irregular Shapes in elastograms. This difference can be obtained in terms of a feature called solidity:

$$\text{Solidity} = \ cvx / \frac{cvx-tumour}{N}$$

Where:

N = The total number of imaging modalities involved

cvx = The area obtained from the convex hull of a tumour

Tumour = the area of tumour

The convex hull is the smallest convex set containing a tumour and resembles a rubber

Comparison of different threshold values with the cumulative threshold value for the ultrasound image1" right lobe of kidney" shown in Table 1

Threshold k	Area	Difference of area w.r.t. k = 6	Solidity	Difference of solidity w.r.t. k=6	Perimeter	Diff of perimeter w.r.t. k=6
4	5153.02	- 1197.66	0.5	- 0.1312	489	- 71
5	5860.35	- 490.33	0.5231	- 0.1081	522	-38
6	**6350.68**	**0**	**0.6312**	**0**	**560**	**0**

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7	6892	541.32	0.6852	0.054	595	35
8	7312	961.32	0.75	0.1188	634	74
9	7818.46	1467.28	0.812	0.1808	731	171
10	8356.63	2005.05	0.9333	0.3021	780	220

Table 1. Texture Feature for Different Thresholds for Image1 Right Lobe of Kidney.

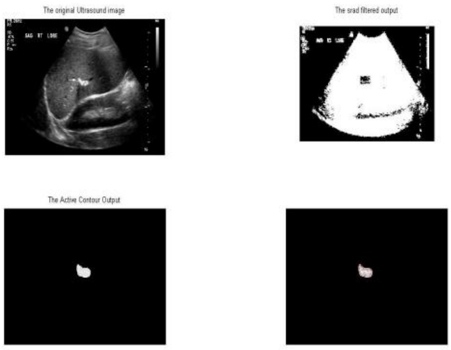

Fig. 1 Ultrasound image of kidey, SRAD Filtered image, Active contour, Segmented image

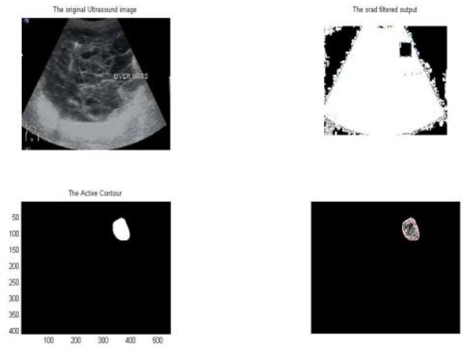

Fig. 2 Image2 "Liver mass" Showing the Lesion Part , SRAD Filtered Image , Active Contoured Image and Segmented Image.

Comparison of different threshold values with the cumulative threshold value for the ultrasound image2 "Liver mass" shown in Table 1.

Threshold K	Area	Difference of area w.r.t. k = 6	Solidity	Difference of solidity w.r.t. k=6	Perimeter	Diff of perimeter w.r.t. k=6
4	5153.02	- 1197.66	0.5	- 0.1312	489	- 71
5	5860.35	- 490.33	0.5231	- 0.1081	522	-38
6	**6350.68**	**0**	**0.6312**	**0**	**560**	**0**
7	6892	541.32	0.6852	0.054	595	35
8	7312	961.32	0.75	0.1188	634	74
9	7818.46	1467.28	0.812	0.1808	731	171
10	8356.63	2005.05	0.9333	0.3021	780	220

Table 2. Texture Feature for Different Thresholds for Image2 Liver Mass

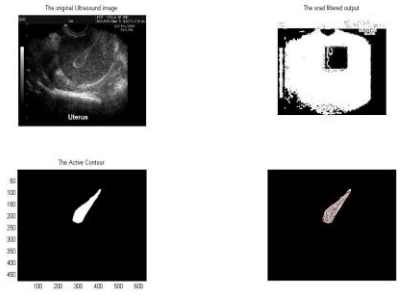

Fig. 3 Image3 "Uterus" Showing the Lesion Part , SRAD Filtered Image , Active Contoured Image and Segmented Image

Comparison of different threshold values with the cumulative threshold value for the ultrasound image3 "Uterus" shown in Table 3

Threshold K	Area	Difference of area w.r.t. k = 8	Solidity	Difference of solidity w.r.t. k=8	Perimeter	Difference of perimeter w.r.t. k=8
4	378	-165.08	0.29	-0.27	308	-172
5	414.65	-128.43	0.327	-0.233	369	-111
6	482.34	-60.74	0.343	-0.217	395	-85
7	509.65	-33.34	0.49	-0.07	423	-57
8	**543.08**	**0**	**0.56**	**0**	**480**	**0**
9	628.76	85.68	0.6133	0.0533	552	72
10	696.23	153.15	0.753	0.193	587	107

Table 3. Texture Feature for Different Thresholds for Image 3 Uterus

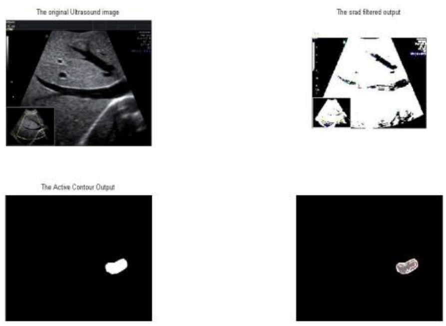

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Fig. 4 Image4 “Liver 2” Showing the Lesion Part , SRAD Filtered Image , Active Contoured Image and Segmented Image.

Comparison of different threshold values with the cumulative threshold value for the ultrasound image4 “Liver 2” shown in Table 4

Threshold k	Area	Difference of area w.r.t. k = 4	Solidity	Difference of solidity w.r.t. k=4	Perimeter	Diff of perimeter w.r.t. k=4
4	**974**	**0**	**1.023**	**0**	**534**	**0**
5	1068	94	1.056	0.033	578	44
6	1123	149	1.093	0.07	590	56
7	1243	269	1.109	0.086	650	116
8	1279	305	1.156	0.133	694	160
9	1365	391	1.188	0.165	707	173
10	1444	470	1.2	0.177	789	255

Table 4. Texture Feature for Different Thresholds for Image4 “Liver 2”

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VIII. Conclusion

We proposed an image segmentation system for ultrasound images. We modified existing techniques and combined them with our proposed procedures to enable accurate detection of objects. The proposed model was tried for different sets of images like kidney, liver, and uterus. These images were segmented successfully

In this proposed method the five sets of images are initially pre-processed by anisotropic diffusion filtering and then by an automatic threshold technique. The level set method is utilized to segment the lesion in the combined image. The area, solidity and perimeter are computed from the segmented lesions. The result of SRAD filter was very accurate it identifies the edges and they are allowed diffuse with the lesion part and remove unwanted speckle completely. We also compared our proposed Automatic threshold method with those threshold values computed manually and calculated their variations in area, solidity, perimeter with respect our proposed method. We can apply ultrasound images directly as input to our method and obtain required accurate results in previous methods there used to need for compressing Ultrasound images which has been eliminated in our method.

Compared with previous approaches, our technique offers many advantages including better accuracy, greater noise reduction, and faster speed. Moreover, our system is fully automatic, thus suitable to integrate into other automate systems. Our method is applicable to broader area not only identifying lesions from liver and uterus but it can also be applied to segment the stones inside the kidney.

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Biography

Hemanth Kumar P. received the Master's degree in Digital Communication from National Institute of Technology (MANIT) Bhopal, Madhya Pradesh, India in the year 2010. Currently working as Assistant Professor in AMC Engineering College, Bangalore in Department of Electronics & Communication Engineering. I have cleared PhD entrance in the stream of Computer Science Engineering from Visvesvaraya Technological University. My area of interest include Neural Network, Data Mining, Image Processing, Communication etc. I have two years of Teaching Experience and guided two M.Tech projects successfully.

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