

BENIGN HEPATIC TUMOR SEGMENTATION ON ULTRASOUND IMAGES

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DECLARATION

I hereby declare that the work which has been presented in the dissertation entitled "**Benign Hepatic Tumor Segmentation on Ultrasound Images**" in partial fulfilment of requirements for the award of degree of Master of Engineering in Electronic Instrumentation and Control Engineering submitted in the Department of Electrical and Instrumentation Engineering at Thapar University, Patiala is an authentic record of my own work carried out under the supervision of **Dr. Deepti Mittal**. It refers others research work which is appropriately recorded in reference section. The matter contained in this dissertation has not been submitted, neither partially nor in full to some other degree to whatever other college and organization aside from as detail in content and references.

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NOMENCLATURE

Main symbols and notations used in this study are listed below. Sometimes a symbol may have alternate meaning but in such a case, the context is sufficient to avoid confusion.

US	Ultrasound
LSM	Level Set Method
DSC	Disc Similarity Coefficient
RVD	Reserve Volume Difference
SRAD	Speckle Reduction Anisotropic Diffusion
AOE	Average Overlap Error
AVD	Average Volume Difference
VOE	Volume Overlapping Error
TPVF	True Positive Value Fraction
FNVF	False Negative Value Fraction
ASD	Average Surface Distance
MSD	Maximum Surface Distance
SI	Similarity Index

ABSTRACT

Benign hepatic tumors are although noncancerous in nature, but if they are not monitored regularly they might cause problems in their latter stages. There are two categories of benign hepatic tumors, first category can be defined as semi-solid masses i.e. sacs like structure filled with fluid and the second category contains tumors that are solid masses. These lesions although do not spread to other parts around the affected area but if the size keeps on increasing it might damage the liver severely. Tumor segmentation is one of the most common non-invasive methods that is used to monitor the tumor size efficiently. Segmentation of hepatic tumor on ultrasound (US) images is a complex task due to intratumoral intensity inhomogeneity and similarity in the tumor appearance with rest of the liver region. Level set method (LSM) is one of the segmentation methods that is capable of performing segmentation on ultrasound images and provide accurate results. This segmentation method is mostly preferred as the curve can split and merge to take the topology of the desired tumor. A higher order function which is usually a distance function is used as a level set function. When this level set function is at zero level, it is marked as the initial curve. Then by using different parameters, image based energy is formulated such that this energy will have minimum value at the tumor boundary. To guide the curve evolution from its initial location towards the tumor boundary efficiently, a regularizing term is added with the image based energy. Based upon different characteristics of solid and semi-solid type of hepatic tumor on US images, two different methods were developed to segment them using LSM. Chan and Vese used Mumford-Shah fitting term by considering intensity variations to develop the image based energy whereas Georgiou *et al.* used distance between the intensity distribution inside and outside the curve as a parameter to segment the desired region. The drawback of these methods was that they were not very accurate on images with intratumoral inhomogeneity and suffers from curve leakage at weak edges at the boundary of the tumor. In the present work, some modifications are introduced in these methods. A shape based stopping criteria is introduced in the method developed by Georgiou *et al.* to avoid leakage problem. The regularization term of both methods are modified to guide the evolving contour towards the exact boundary of the tumor. The result of modifications introduced clearly demonstrates that they outperform the original methods. The proposed method is also compared with existing segmenting methods in terms of disc similarity coefficient and relative volume difference to show the high accuracy and reliability of the present work.

CHAPTER 1

INTRODUCTION

1.1 Overview

Liver is one of the essential organs in human body. It is situated in the upper right side portion of the abdomen. The main function of the liver is to filter toxics from the blood coming from digestive system and then send it to rest of the body. Hepatic tumor is most common liver disease which if not treated in the initial stages, may alter the working of the liver or even cause permanent damage. Ultrasound (US) is the most preferred imaging modality for the detection of hepatic tumors as it is cost-effective, non-invasive and has portable support. Tumor segmentation means to separate the tumor region from the background region based upon its characteristics like intensity, texture, colour etc. The segmentation helps in monitoring the size of the tumor, its location in the liver, shape of the tumor and many more parameters that helps in diagnosis and guides the physician in adopting effective measures while treating the patient. Hepatic tumor segmentation is a tedious task due to inconsistency in the shape and intensity values of the tumor making the noticeable changes between healthy liver tissues and tumor difficult. Alternatively, segmentation on ultrasound images is itself a challenging task due to acoustic interference of spackle and other artifacts that are inherent in these images. Therefore, there is a requirement of more accurate and efficient tumor segmentation method.

Manual segmentation of hepatic tumor on US images is a monotonous work which is time consuming and the accuracy of the segmentation highly depends upon the knowledge and experience of the clinician. The process of tumor diagnoses is made more accurate and efficient by providing the clinician a computer aided segmentation algorithm. Level set method (LSM) is one of the widely adopted computer aided segmentation algorithm used to segment hepatic tumor on US images. This method is capable of detecting exact shape of the tumor as it can split or merge according to the tumor topology. Two level set methods are studied and modified to get more accurate segmentation results of benign hepatic tumor.

1.2 Background and significance

1.2.1 Liver

Liver is wedge in shape, reddish-brown coloured organ which is located in the upper right side of the human body [1]. The liver can be broadly divided into four lobes namely left lobe, right lobe, caudate lobe and the quadrate lobe as shown in the fig. 1.1.

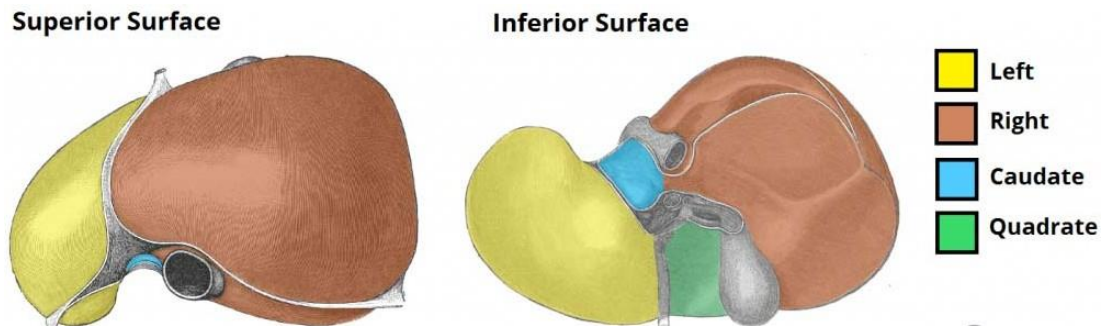


Fig. 1.1- Anatomy of a liver

Liver is one of the most essential organs in the body as it performs many functions like:

- Bile production and excretion.
- Metabolism of fats, proteins, and carbohydrates
- Activation of enzymes used for different body processes.
- Storage of glycogen, essential vitamins and minerals.
- Synthesis of plasma proteins.
- Detoxification and purification of blood.

1.2.2 Hepatic tumors

Hepatic tumors are swelling in the liver region caused due to abnormal growth of tissues that creates either solid masses or fluid filled sacs [2]. Hepatic tumor can either be malignant or benign. Benign tumor although do not spread to other body parts like malignant tumors but can still cause problems if not monitored frequently [3]. During the diagnoses of a tumor, when a tumor is affirmed to be benign, it is usually not considered as dangerous and left unmonitored. This approach sometimes results in a catastrophe as the tumor might increase in size and can press the blood vessels or other structures around the tumor.

Common benign hepatic tumors can be classified as solid masses and fluid filled semi-solid masses [4]. Hemangioma is one of the most common benign hepatic tumors. Hepatic hemangioma is a solid mass present in the liver, made up of tangled blood vessels. It occurs in 7% to 25% of the population [5]. Usually a hemangioma of diameter less than 5 cm may develop inside the liver of a human being. Multiple hemangiomas can also be found in around 10 to 30% cases. Most of the cases of hemangiomas are asymptomatic thus do not require treatment but regular follow up and monitoring is needed to avoid any further complications.

However, a hemangioma may need to be removed surgically if it is large enough and shows symptoms like pain in the upper right quadrant of the abdomen, abdominal bloating or nausea [6]. Other complications associated with hepatic hemangioma are spontaneous or posttraumatic rupture which results in acute hemorrhagic shock [7]. Hepatic cysts are abnormal, fluid-filled bubble like-structures that may develop in the liver approximately from 2% to 7% of the population [8-9]. Not more than 10-15% of these patients have symptoms that bring the cyst to the clinical attention. Generally cyst do not cause any problem thus, do not require invasive treatment but if the size keeps on increasing the patient develops symptoms like upper abdominal fullness, discomfort, or pain. Sometimes the size may become very large causing damage to the tissues of the liver thus the patient may even bleed into the cyst. This then causes sudden and severe pain in the upper quadrant of the body [10].

1.2.3 Ultrasound imaging technique

Ultrasound imaging utilizes high-frequency sound waves to examine the parts that are inside the body thus this is a non-invasive method used for diagnosis [11]. Since ultrasound images are acquired in the real-time, they can be used for monitoring movement of the internal organs of the body. It does not expose the subject to the ionization radiations like X-ray imaging, thus it is safer imaging modality. Being portable in nature, it is very feasible to use as the instrument can be brought bedside near the patient. This imaging modality is substantially low in cost compared to other medical imaging modalities. Ultrasound imaging is not time consuming as MRI technique where the patient has to lie still for long duration.

US is a preferred imaging modality for the diagnosis and identification of the hepatic tumors due to their prominent characteristics on US images. Hepatic cyst has characteristic appearance of bright walls and dark centres on ultrasound images. Similarly hepatic hemangioma is typically characterized as hyperechogenic well defined regions with posterior acoustic enhancement on ultrasound images [12]. The appearance of the larger hemangiomas is highly heterogeneous because of complications like thrombosis, calcification, or haemorrhage [13-15]. Some hemangiomas are round in shape with echoic border and heterogeneous appearance. Figure 2 shows the characteristic features of normal liver along with hepatic cyst and hepatic hemangioma on US images.

1.3 Motivation

Benign hepatic tumors are although noncancerous asymptomatic in nature, but their size may increase if there is a significant amount of blood flowing into the tumor. Increasing size of the tumor causes lots of pain and even might damage some parts of the liver. Depending upon

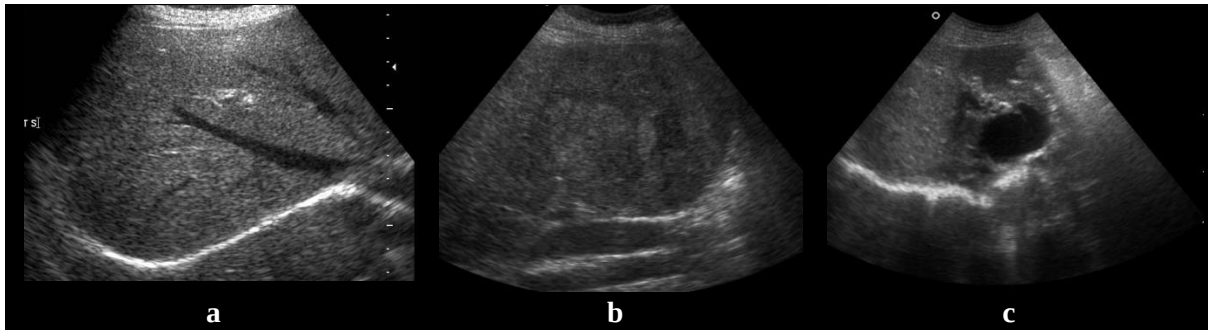


Fig. 1.2- Appearance characteristics of (a) normal liver (b) hepatic hemangioma (c) hepatic cyst on ultrasound images

the amount of damage caused by the tumor the doctor may decide to remove the entire affected section or even a liver transplant may be required [7]. Early detection and regular monitoring is thus important for the patients having these lesions. The idea of the amount of change in the size of the tumor will help the doctor to decide what measures are to be taken to treat the patient. Manual monitoring of the change in the size of the tumor by the expert depends on his ability and experience in this work, it is very time consuming and the clinician might get tired and cause errors. An accurate and precise monitoring of the size of a tumor can be done by a computerized tool that is capable of segmenting the tumor portion from an image. Number of pixels from that segmented tumor portion can be counted automatically and thus the clinician can monitor the variations very minutely.

1.4 Main contributions

Present work illustrates computer aided segmentation methods that are used to extract benign hepatic tumors. First Chan-Vese level set method is modified to segment hepatic cysts which have almost homogeneous intensities inside the cystic region with bright boundaries. Then different level set approach is used and modified to segment hepatic hemangioma which is heterogeneous in nature. The experiments were conducted on 67 US images which consisted 17 cystic and 50 hemangioma cases.

The objective of this work is to perform accurate segmentation by preserving the definitions of tumor. This is achieved by:

- (i) Introducing more number of pixels to calculate the local derivatives along the curve to monitor the curve evolution more minutely by modifying the regularization term. This regularization term that is used to keep the evolution of the curve smooth by preventing sharp curves.
- (ii) The accuracy of the segmentation methods also depends upon the initialization of the curve. Prior knowledge of the shape of the tumor is used to modify the shape of the initialize curve to improve the accuracy of the segmentation results to meet the requirement of the clinician.
- (iii) A shape based stopping criteria is introduced to guide the curve evolution towards the exact boundary and to avoid the leakage of the curve at the weak edges of the tumor boundary.

1.5 Thesis overview

In the present work, level set methods are used to segment benign hepatic tumors on ultrasound images. Chan-Vese method is modified to extract hepatic cysts on ultrasound images and distribution metric based level set method using shape based stopping criteria is proposed to segment hepatic hemangiomas which are inhomogeneous intensity type solid masses in the liver. The dissertation work is presented chapter wise covering introduction to the problem, contribution of the work and motivation for this work in chapter 1. Chapter 2 highlights the previous research work done in the tumor segmentation area of medical image analysis domain. The basics of level set method and the formulation of Chan-Vese level set method and the Distribution metric based level set method are explained in chapter 3. The modifications done along with their brief steps are explained in chapter 4 followed by the experimental setup details which include the description of the dataset and the software used along with the evaluation parameters used to analyze the segmentation methods in chapter 5. The segmentation results obtained using level set methods are illustrated in chapter 6 along with related discussions. The entire work along with the future scope is summarized in the end in the conclusion part.

CHAPTER 2

LITERATURE REVIEW

2.1 Tumor Segmentation methods

Tumor segmentation means to separate the tumor region from the background region. This can be a tedious task due to various factors, such as spatial variations in illumination, imperfections of imaging devices, intensity variations and presence of noise and artifacts. Segmentation of tumor on ultrasound images may be significantly complicated task due to intratumoral intensity inhomogeneities and presence of speckle and other artifacts. There are several methods which have been developed to segment tumors on various medical images. Thresholding is one of the primeval techniques that is used for segmentation purpose. Basically it marks all pixels whose intensity values are higher than threshold to tumor region and all the remaining pixels to a background region. Moltz *et al.* [16] proposed a hybrid segmentation method in which they combine thresholding along with morphological processes. Although they achieved accuracy upto 92% they faced difficulties while segmenting the images that are inhomogeneous in nature as they considered intensity variations globally and not locally. Cao *et al.* [17] proposed a segmentation method in which they considered local variations in the intensities as well as the location of the tumor using the iterative relative fuzzy connectedness algorithm. The results were better than thresholding techniques but the accuracy was low on images that had heterogeneous intensity features. Yan *et al.* [18] proposes a semi-automatic segmentation method using watershed transformation. This method performs segmentation on 3D lesions by using this marker based algorithm. Massoptier and Casciaro [19] proposed a novel fully automatic segmentation method that used statistical-based approach to overcome leakage problems. This method also used gradient vector flow based active contour. Li *et al.* [20] introduced level set method based upon minimizing the energy function formulated using local likelihood approximation of the density distribution of the tumor and the multimodal density distribution of the background region. The limitation of this method was leakage of the contour at the weak boundaries of the tumor. Jain and Kumar [21] proposed a method for tumor segmentation in which maximum difference between two regions in a window around the centre pixel is calculated. These region difference filters are applied on the entire image to create region difference image. Converting the region difference image into binary image, morphological operations are used to segment the tumor region. This method does not perform well on the

tumor that does not have well defined boundaries and has heterogeneous appearances. Milko *et al.* [22] conducted experiments on ultrasound images using dynamic texture rather than using static features for the segmentation of hepatic tumor. The textural dynamics of each pixel are designed as an auto regressive process with Gaussian noise. The linear coefficients and noise variance are estimated pixel-wise and a parametric space is comprised in which classification of each pixel is performed. Thus grouping similar pixels together and performing the segmentation. Zhu *et al.* [23] designed a method for segmentation of liver cyst on ultrasound images combining Wellner's thresholding algorithm with particle swarm optimization. Using this method, first an optimal parameter is obtained which binaries the gray image into dark objects and white background. The gray is image obtained using Wellner's thresholding algorithm by PSO method.

Table 2.1 - Previous years research work on segmentation of hepatic tumors on ultrasound images.

Ref	Dataset	Pre-Segmentation processing technique	Segmentation technique used	Evaluation parameters	Pros	Cons
[24]	30	Thresholding	Iterative Fuzzy C-Mean	T=14.25s	Over comes the problem of non-uniform distribution of centroids as seen in FCM methods.	Boundary details are not clear due to presence of speckle.
[21]	56	- Alpha-trimmed mean filter. - Region-Difference filter. - Thresholding	Morphological operations.	T=5.05s	Computational time is less thus can be used in real-time applications.	Unable to segment tumours with weak boundaries and heterogeneous appearance on ultrasound images.
[22]	12		- Auto regressive technique. - Maximum a Posteriori	DSC=79%	- Useful for real-time applications. - No pre-processing required.	The number of images used for evaluation of the method is very less.
[23]	92	Filtering Thresholding Morphological operations	Wellner's thresholding method. Particle swarm	TPVF=95% FNVF=4.9%	Adaptive thresholding is designed.	Experiment performed only on cystic images.

			optimization			
T= computational time, DSC= Disc Similarity Coefficients, TPVF= True Positive Value Fraction and FNVF= False Negative Value Fraction						

2.2 Segmentation work on Level set method

Level set method (LSM) is one of the most popular methods used for tumor segmentation on ultrasound images as it is capable of segmenting tumors with intensity heterogeneity and can split or merge according to the topology of the tumor. This method was introduced by Osher-Sethian [25], and is capable of identifying weak boundaries of the tumor as it uses a deformable segmenting curve which evolves by minimizing an energy function. This energy function can be formulated using diverse parameters obtained from the image. Depending upon the application and characteristics of the desired tumor region on ultrasound image, the parameter can be either edge based or region based. Therefore, LSM can be broadly classified as edge based LSM or region based LSM. Caselle *et al.* [26] proposed a new method for segmentation, that formed the energy function using the gradient of the image as the edge-detector. While evolving, the curve splits and merges, detecting both interior and exterior boundaries. This edge based method is inappropriate for segmentation of tumor on ultrasound images due to presence of speckle, tumors with incomplete boundaries, low contrast between the tumor and the background. Thus the segmentation of tumor on ultrasound images is generally performed using region-based LSM. Tsai *et al.* [27] proposed a region based level set method in which Mumford-Shah energy functional was used along with gradient flow to segment the required region. Similarly, Chan and Vese [28] introduced a region-based segmentation model using Mumford and Shah functional. This method uses global constraints to minimize the region based energy function, which provides robustness to the initial location, size and shape of the mask. The main drawback of using global constrain is that it does not perform proper segmentation in the cases of heterogeneous intensity areas. Zheng *et al.* [29] proposed an improvement in the Chan and Vese method by introducing a local constraint using local neighbourhood information. This improvement allowed monitoring the changes in the intensity value in local neighbourhood thus improving the segmentation results. Wang *et al.* [30] introduced a new segmentation method that is based upon maximum a posterior using gaussian distribution to model local images intensities.

A hybrid model that uses both local and global constraints on the energy function obtains more accurate segmentation as it utilizes the benefits of both methods. These methods not only provide robustness to the initialization but also detect minute variations in the region

Table 2.2 - Previous years research work on segmentation using level set method.

Ref	Image type	Level set method	Approach	Evaluation Parameter
[36]	Synthetic images	Shape based LSM	Edge based	
[37]	10 clinically acquired CT images	Local constraint based LSM	Edge based	AOE=32.6% AVD= 17.9%
[38]	Synthetic images	Multi threshold based LSM	Edge based	
[39]	MR images	Intensity based LSM	Region based	
[40]	2 CT images	Integrated image gradient based LSM	Region based	• AOE= $12.75 \pm 5.76\%$ • RAD = $4.28 \pm 9.58\%$ • ACD= 1.66 ± 1.09 mm • MCD= 4.29 ± 2.75 mm
[41]	15 CT images	hybrid LSM	Region based	• SI = $97.6 \pm 0.5\%$ • FPE = $2.2 \pm 0.7\%$ • FNE = $2.5 \pm 0.8\%$ • ASD = 1.4 ± 0.5 mm • Ct= 77 ± 10 s
Average overlap error =AOE, Average volume difference =AVD, Volume overlapping error =VOE, Relative volume difference=RVD, Average surface distance=ASD, Maximum surface distance=MSD, Similarity index=SI, False positive error=FPE, False negative error=FNE, Computation time=Ct				

with intensity inhomogeneity. One such method was introduced by Georgiou *et al.* [31] that formulates the energy function based upon the probability density value of the intensity to construct a distribution metric. The distribution metric is represented as the distance between the intensity distributions of two regions, which is to be maximized to obtain the boundary of the tumor on ultrasound images. This method obtains accurate results on most of the cases, but in the case with heterogeneous intensity with very less variations in the tumor and the background the accuracy of this method decreases. This happens due to leakage of the evolving curve at the weak boundaries.

Object based parameters are usually used to overcome the leakage at weak boundaries. Shape size and location of the tumor are such object parameters. These parameters provide local constraint to the evolving curve thus by improving the segmentation results. Shape of the tumor is one of the most commonly used parameter, as with the prior knowledge of the shape of the tumor a statistical shape model can be approximated and the automated procedure then tries to find the region that fits the shape model perfectly. This can be achieved either by

initializing the curve similar to that of the tumor or to introduce a shape based stopping criteria. Initial shape and location of the curve is an important parameter as if not properly decided the curve may converge to local minima that does not defines the required tumor region. Tsai *et al.* [32] proposed a method that uses shape based approach to initialize the curve. A parametric model is formulated using level set method by applying principal component analysis to initialize the required shape of the curve using signed distance function. A similar work was introduced by [33]. Dambreville *et al.* [34] introduced a new method for segmentation using principal component analysis kernel to introduce a shape based constraint to monitor the convergence of the curve towards the required region. This method combines the prior knowledge of the shape with the level set method to segment the exact tumor boundary. Cremers *et al.* [35] introduced a shape based segmentation method by introducing shape statistics into the Mumford-Shah energy functional, thus applying a stopping criteria guide the evolution of the curve.

The brief study of state of the art methods provides an overview about the limitations of the existing segmentation methods. Leakage of the evolving curve at the weak boundaries, incapability of segmentation of the region with intensity inhomogeneity, affects of the initial shape of the curve etc. are to state a few of them.

CHAPTER 3

LEVEL SET METHOD

The majority of the segmentation methods that used to extract hepatic tumors on US images are incapable to detect exact boundary of the tumor due to irregular shape and weak edges of the tumor boundaries with inhomogeneous intensity variations. LSM has some inherent properties that helps it to overcome these difficulties.

3.1 Introduction to level set method

Level set method is a conceptual method that uses level set functions as a mean to analyze surfaces and shapes numerically. This is an implicit representation of deformable curves which instead of using parameters to represent a curve, uses a function known as level set function to represent the curve. Wherever the value of this level set function is zero also known as zero level set, the level set function is marked as the curve. Osher and Sethian [25] introduced the LSM in which they considered $\varphi(x, y, t)$ as the higher order level set function. They stated that $\varphi(x, y, t)$ is a distance function where $\varphi(x, y, t) = 0$ represents the curve $C(x, y)$ implicitly and $\varphi(x, y, t) > 0$ is the region outside the curve and $\varphi(x, y, t) < 0$ is the region which is enclosed by the curve. The evolution of the curve $C(x, y)$, towards the required boundary is guided by a energy term $\vec{v}$. This energy term depends upon the image based information such as the intensity value, texture colour, shape etc. They defined a PDE, which is to be minimized to segment the required region.

$$\frac{\partial \varphi}{\partial t} + \vec{v} \cdot \nabla \varphi = 0 \quad (3.1)$$

3.2 Chan-Vese Level set method

Chan-Vese [28] proposed a LSM in which the segmentation is done by minimizing an energy function based upon Mumford- shah segmentation functional. Consider an image $I(x, y)$, in which the region to be segmented is characterized by different intensity values and the other parts of the image with different intensity values. Let B_0 be the boundary of the desired region that needs to be segmented. Chan and Vese used signed distance function to compute the higher order level set function $\varphi(x, y, t)$. The initial curve $C(x, y)$ was marked where the value of the level set function $\varphi(x, y, t)$ was zero. Similarly following level set formulation given by Osher and Sethian, they also considered that the region inside the curve is the region where $\varphi(x, y, t) < 0$ and the region outside the curve is the region with $\varphi(x, y, t) > 0$.

The image based energy was formulized using Mumford-Shah fitting terms. They considered variation in the intensity values inside and outside the desired region to be the parameter to compute the image based energy. This was achieved by calculating the average intensity value C_{in} inside the curve and C_{out} is the mean intensity value outside the curve. The fitting term $F(C)$ was then derived as

$$F(C) = F_{in} + F_{out} \quad (3.2)$$

$$F(C) = \int_{inside(C)} |I(x, y) - C_{in}|^2 + \int_{outside(C)} |I(x, y) - C_{out}|^2 \quad (3.3)$$

Discretizing this energy function and writing it as a pixel wise function gives:

$$F(x, y) = |I(x, y) - c1|^2 + |I(x, y) - c2|^2 \quad (3.4)$$

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 $C(x, y)$ will be at B_0 . A regularizing term is also added with the fitting terms to make the evolution of the curve smooth.

3.2 Distribution Metric method

Georgiou *et al.* [31] introduced a new LSM which was based upon distribution metric method and performs segmentation by minimizing an energy function that is formalized by using image based energy with a smoothening regularizing term.

Image based energy

The image based energy plays a vital role in this segmentation method, since it is accountable for driving the curve towards the tumor boundary. This energy function is formulated using both global constraints as well as the local constraints to achieve required segmentation results. Let $I(x, y)$ represents an input image, where $x, y \in \mathbb{R}^2$ specifies the coordinate of a pixel in the image plane. Let $I : \mathbb{R}^2 \rightarrow \mathbb{A}$ is the mapping from the image which is defined over a domain γ to a domain of a photometric parameter α i.e. the intensity value. Thus the

mapping from image plane to the photometric plane transforms I into a grey scale image. The photometric parameter α is a vector containing intensity values in the range of 1 to 256.

A binary mask is created near the tumor region with the intention to cover the entire tumor region with a mask. Signed distance function $\phi : \mathbb{R}^2 \rightarrow \mathbb{R}$, is calculated for this mask and treated as the level set function in this method. Zero level, where the value of this function ϕ is zero, is marked as curve C . The region outside the curve C is represented by $\phi > 0$ whereas the region inside the curve C is represented by $\phi < 0$.

Cumulative distribution function F for the region w i.e. enclosed by the curve C , with the enclosed area defined as A_{in} is defined using Heaviside function as:

$$F(\alpha) = \frac{\iint_w H_\epsilon(\alpha - I(x, y)) dx dy}{A_{in}} \quad (3.5)$$

The relationship between cumulative distribution function $F(\alpha)$ and probability density function $R(\alpha)$ is:

$$R(\alpha) = \partial(F(\alpha)) \quad (3.6)$$

Thus, the probability density function $R_{in}(\alpha)$ of the region w can be defined as:

$$R_{in}(\alpha) = \frac{\iint_w \delta_\epsilon(\alpha - I(x, y)) dx dy}{A_{in}} \quad (3.7)$$

where, δ_ϵ is the Dirac delta function which is the derivative of the Heaviside function. Considering the entire image γ , the required region i.e. the region inside the curve can be defined by introducing the function ϕ in the above equation. This term is introduced with the help of Heaviside step function H_ϵ which varies with the value of ϕ .

$$R_{in}(\alpha, \phi) = \frac{\iint_\gamma \delta_\epsilon(\alpha - I(x, y)) \cdot H_\epsilon(-\phi(x, y)) dx dy}{\iint_\gamma H_\epsilon(-\phi(x, y)) dx dy} \quad (3.8)$$

where,

$$H_\epsilon(\phi) = \begin{cases} 1 & \phi > \epsilon \\ 0 & \phi < -\epsilon \\ \frac{1}{2} \left(1 + \frac{\phi}{\epsilon} + \frac{1}{\pi} \sin\left(\frac{\pi \cdot \phi}{\epsilon}\right) \right) & \text{otherwise} \end{cases} \quad (3.9)$$

$$\delta_{\epsilon}(\phi) = \begin{cases} 0 & \phi > \epsilon \text{ or } \phi < -\epsilon \\ \frac{1}{2\epsilon} \left(1 + \cos\left(\frac{\pi \cdot \phi}{\epsilon}\right)\right) & \text{Otherwise} \end{cases} \quad (3.10)$$

Similarly, the probability density function of intensity outside the curve can be calculated as:

$$R_{out}(\alpha, \phi) = \frac{\int_{\gamma} \delta_{\epsilon}(\alpha - I(x)) \cdot H_{\epsilon}(\phi(x)) dx}{\int_{\gamma} H_{\epsilon}(\phi(x)) dx} \quad (3.11)$$

Image based energy, which is basically represents the distance as the standard deviation between the log-likelihood of two distributions i.e. PDFs inside and outside the curve. The log-likelihood between two regions increases as the curve separates the two regions and is defined as:

$$D(\alpha, \phi) = \sqrt{E \left\{ \int_{\gamma} \left(\log \frac{R_{in}(\alpha, \phi)}{R_{out}(\alpha, \phi)} \right)^2 \right\} - E \left\{ \left(\int_{\gamma} \left(\log \frac{R_{in}(\alpha, \phi)}{R_{out}(\alpha, \phi)} \right) \right)^2 \right\}} \quad (3.12)$$

where the latter term denotes the standard deviation of the difference

$$\log(R_{in}(\alpha, \phi) - \log(R_{out}(\alpha, \phi))) \quad (3.13)$$

Computing the gradient (∇D) by using calculus of variations and taking the first variation with respect to ϕ , we arrive at the following equation

$$\nabla_{\phi} D = \frac{\delta \epsilon}{D} \times [E\{T \times G\} - E\{T\} \times E\{G\}] \quad (3.14)$$

where

$E\{f(\alpha)\}$ is the expected value of the function $f(\alpha)$ with respect to the photometric variable α and T is the local constraint defined by:

$$T = \log \frac{R_{in}(\alpha, \phi)}{R_{out}(\alpha, \phi)} \quad (3.15)$$

whereas G defines the global constraint of the image based energy

$$G = \left[\left(\frac{1}{A_{in}} + \frac{1}{A_{out}} \right) - A(\alpha - J(x, y)) \left(\frac{1}{A_{in}P_{in}(\alpha, phi)} + \frac{1}{A_{out}P_{out}(\alpha, phi)} \right) \right] \quad (3.16)$$

The regularization term

The regularizing term is introduced into the level set method to restrict the evolution of the curve towards the required tumor region. This term helps to maintain small value of the curvature of the curve to avoid sharp turns and sudden disappearance of the curve. This term not only regularizes the smoothness and the direction of the curve evolution but also contributes in the speed of the evolution. The curvature of the curve is used as the regularization term in this method and is calculated using central difference method as:

$$curvature = \frac{F_X F_{YY} - F_Y F_{XX}}{(F_X F_X + F_Y F_Y)} \quad (3.17)$$

where, 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.

$$e = \nabla_{phi} D + \beta \cdot Curvature \quad (3.18)$$

Image based energy is combined with the curvature to form a dynamic energy function that is to be minimized for the evolution of the curve for accurate segmentation of the tumor.

CHAPTER 4

BENIGN HEPATIC TUMOR SEGMENTATION METHODS

4.1 Segmentation of hepatic cyst using modified Chan-Vese method

A regularizing term which is usually added to the image based energy to restrict the evolution of the curve towards the required tumor region. This term constraints the evolution of the curve in the normal direction of its curvature. The regularization term also helps to maintain small value of the curvature of the curve to avoid sharp turns and sudden disappearance of the curve.

The Chan-Vese method used curvature of the evolving curve to regulate the curve evolution and to avoid sudden sharp turns resulting leakage of the curve at weak edges of the boundary. They used central difference method to calculate the curvature of the evolving curve.

$$curvature = \frac{F_X F_{YY} - F_Y F_{XX}}{(F_X F_X + F_Y F_Y)} \quad (4.1)$$

Where where, 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.

$$F_X = \frac{F_{(i+1,j)} - F_{(i,j)}}{2\Delta X} \quad (4.2)$$

$$F_Y = \frac{F_{(i,j+1)} - F_{(i,j)}}{2\Delta Y} \quad (4.3)$$

$$F_{XX} = \frac{F_{(i-1,j)} - 2.F_{(i,j)} + F_{(i+1,j)}}{(\Delta X)^2} \quad (4.4)$$

$$F_{YY} = \frac{F_{(i,j-1)} - 2.F_{(i,j)} + F_{(i,j+1)}}{(\Delta Y)^2} \quad (4.5)$$

Taking inspiration from the outstanding work of Mittal *et al.* [14], where the higher order pixels are used to improve the definition of texture in ultrasound images, the present work proposes a modification in the original method by increasing the size of the local window of pixels to calculate the curvature term. By introducing more number of pixels to calculate

local derivatives along X and Y direction, minute variations in the curvature of the evolving curve can be monitored resulting in effective and efficient convergence of the curve towards the desired tumor region and removing any chances of curve leakage at the weak edges of the tumor. Figure 4.1 illustrates the results of this modification, fig. 4.1 clearly shows the evolution of the curve with the red line and yellow arrows indicated the leakage of the curve using Chan-Vese method.

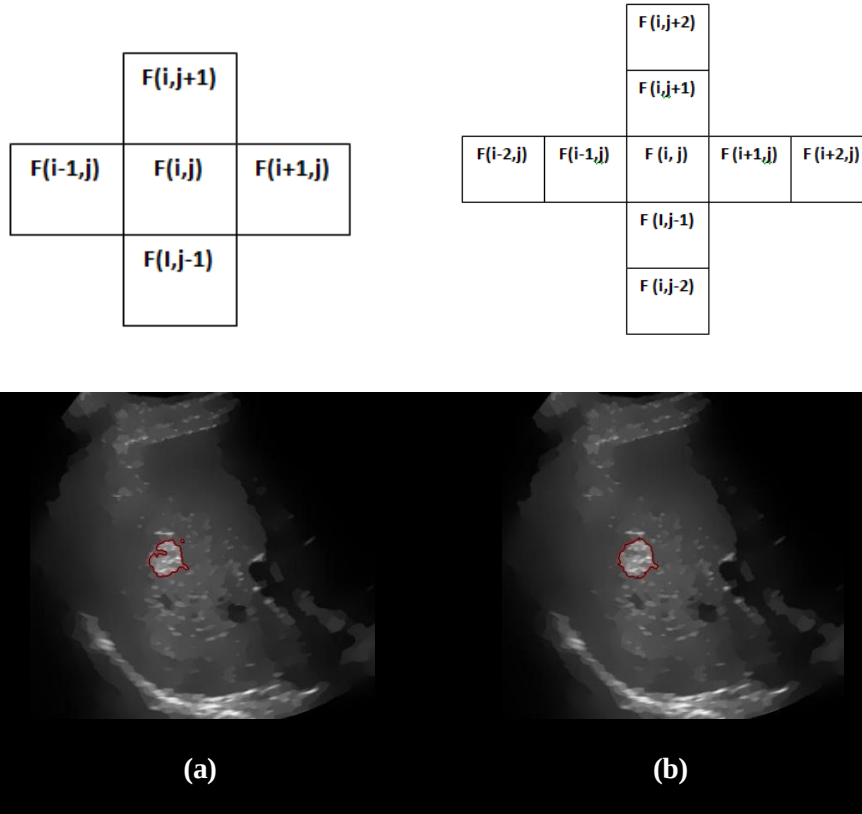


Fig. 4.1 -A comparative analysis of three point central and five point central difference on ultrasound tumor image:(a) template used in three point central difference scheme and its implementation on ultrasound tumor image and (b) template used in five point central difference scheme and its implementation on ultrasound tumor image. Red lines-Contour evolution using level set method.

By including more number of pixels the formula of the local derivatives are given as:

$$F_X = \frac{F_{(i-2,j)} - 8.F_{(i-1,j)} + 8.F_{(i+1,j)} - F_{(i+2,j)}}{12\Delta X} \quad (4.6)$$

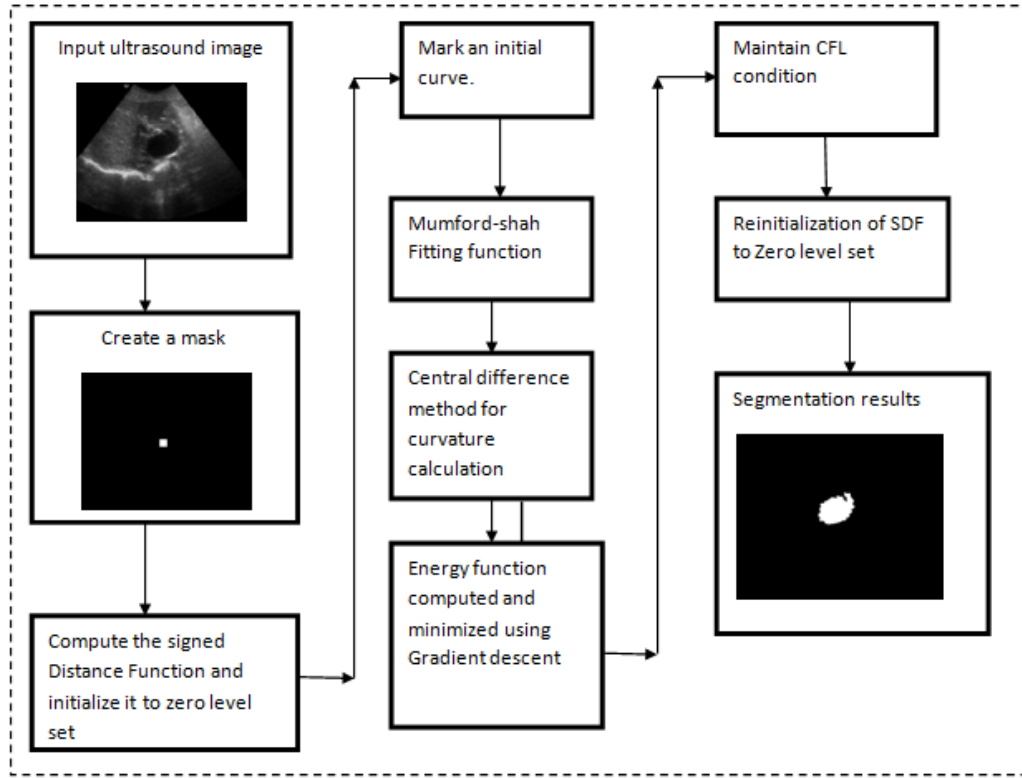
$$F_Y = \frac{F_{(i,j-2)} - 8.F_{(i,j-1)} + 8.F_{(i,j+1)} - F_{(i,j+2)}}{12\Delta Y} \quad (4.7)$$

$$F_{XX} = \frac{-F_{(i-2,j)} + 16.F_{(i-1,j)} - 30.F_{(i,j)} + 16.F_{(i+1,j)} + F_{(i+2,j)}}{12.(\Delta X)^2} \quad (4.8)$$

$$F_{YY} = \frac{-F_{(i,j-2)} + 16.F_{(i,j-1)} - 30.F_{(i,j)} + 16.F_{(i,j+1)} + F_{(i,j+2)}}{12.(\Delta Y)^2} \quad (4.9)$$

The steps that are followed for segmentation of hepatic tumor using modified Chan-Vese method are summarized in brief in fig 4.2 and explained 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 .
- 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.
- Step4: Signed distance function (SDF), ϕ of the mask is computed using the Euclidean distance and is initialized to zero level set. Using ϕ , the initial contour is marked.
- Step5: 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.
- Step6: 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).
- Step7: The curvature of the curve is calculated using the central difference method and is given by the formula.
- 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.
- Step9: The minimization involves convergence of finite differences for which Courant-Friedrichs-Lewy (CFL) condition is maintained.



Step10: 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.

Step11: 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.

4.2 Segmentation of hepatic hemangioma using modified distribution metric method

The proposed method designs a level set method by utilizing the statistical and geometrical information from the ultrasound image into one dynamic energy function to segment the desired tumor portion. The evolution of the curve is constrained at the exact boundary of the tumor by incorporating the shape based stopping criteria. Proposed method can be implemented in three phases, i.e., pre-segmentation processing, segmentation and post segmentation processing. Figure 4.3 explains these three phases in brief which are explained in detail in this section as follows.

4.2.1 Pre-segmentation Processing:

Segmentation of tumor on ultrasound images is a challenging task, due to presence of speckle. It inherently exists in the ultrasound images due to undesirable interference of the scattered light from the soft tissues. Speckle is treated as granular noise in the problem related to segmentation on ultrasound images as it diminishes the fine details of the tumor and also decreases the image resolution. Thus affecting the visibility of the boundary and degrading the quality of segmentation on ultrasound images. Several methods, such as median filter, averaging filter, gaussian filter etc., have been used to remove the speckle from the ultrasound images. However, among them Speckle Reduction Anisotropic Diffusion (SRAD) filter is widely applied and acceptable method by the researchers to reduce speckle. The SRAD filter improves the quality of ultrasound images in order to produce more reliable and effective segmentation results for clinical purposes. Therefore in the present work, SRAD method is applied to reduce the effect of speckle in the pre-processing step.

The effective implementation of any segmentation algorithm depends on the clear visibility of the boundary details of the tumor. Therefore SRAD filter is applied to reduce the speckle up to a limit where the boundary of the tumor on de-speckled image is better delineated than that on the original ultrasound image. This is assured by varying the number of times SRAD algorithm is applied on an ultrasound image. The number of iterations is decided as per the difference in mean intensity values inside and outside the tumor region. The application of SRAD in the pre-processing phase is carried out in the following steps:

Step 1: Read the input image, I .

Step 2: Select a point P_{in} , inside the tumor region and similarly select a point P_{out} , form the background region of the tumor.

Step 3: Find the mean intensity value for 5x5 pixels region around P_{in} , as $Mean_{in}$ and similarly mean is calculated around the point P_{out} as $Mean_{out}$

Step 4: Set the threshold value Th .

Step 5: Find the absolute difference d . Compare the value of absolute difference from the threshold.

$$d = Mean_{in} - Mean_{out} \quad (4.10)$$

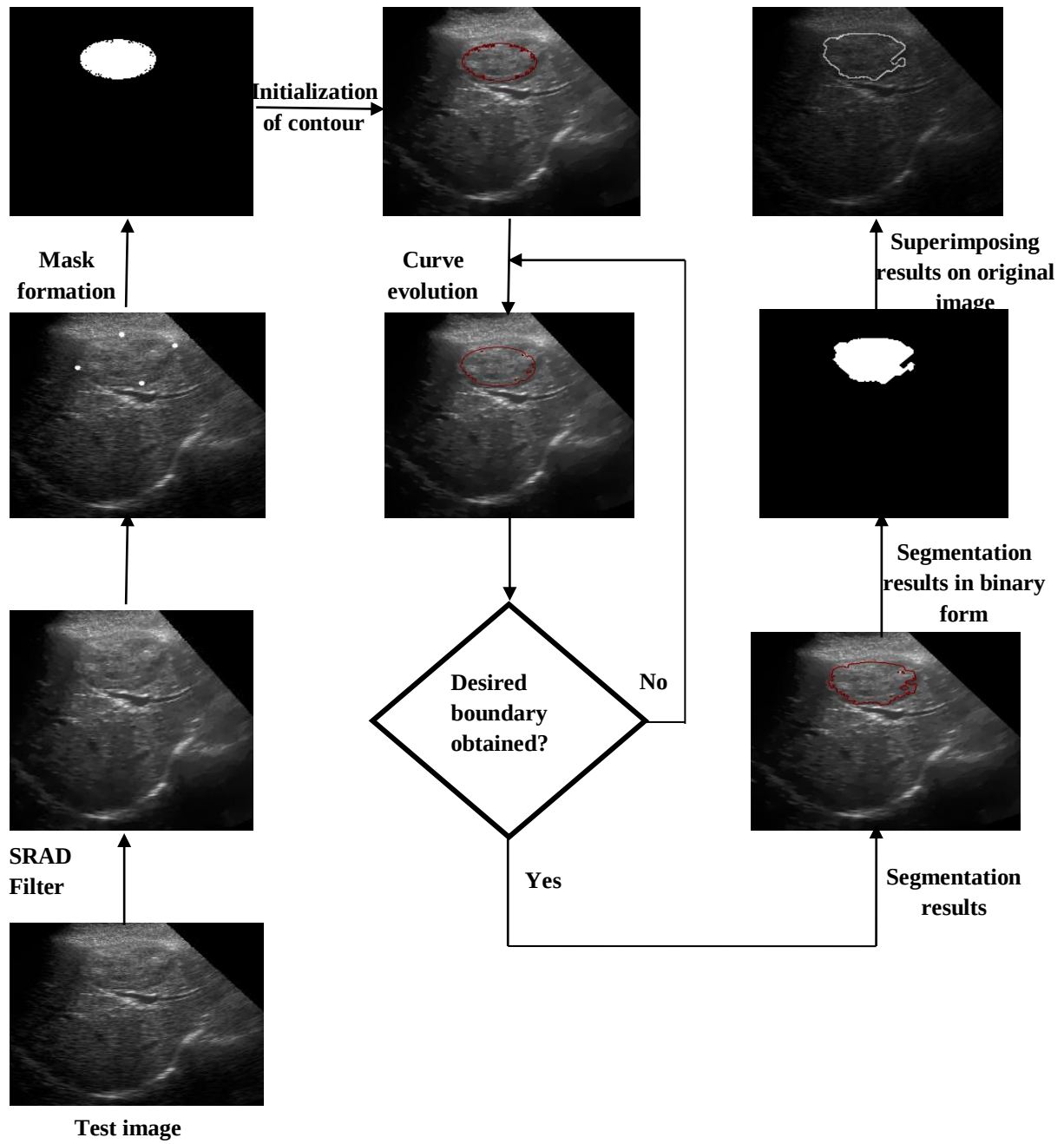


Fig 4.3- Main steps of the segmentation method used for segmentation of hepatic hemangioma.

Step 6: If the value of d is more than the threshold value, apply SRAD using 250 iterations else use number of iterations as 200. The image obtained after pre-segmentation processing phase is denoted by J .

4.2.2 Segmentation

A modification in already existing distribution metric method [21] is proposed in this work for the effective segmentation of the benign tumor. The proposed modification is clearly

described in this section followed by the brief description of the original distribution metric method. The proposed method states modification in the regularization term as well as the image based energy. Introduction of a shape based stopping criteria is also proposed to constrain the evolution of the curve closer to the boundary of the tumor.

Modified regularization term

As explained in section 3.1 more number of pixels are introduced in the neighbourhood of the pixel to monitor the variations in the intensity more precisely to regulate the curve evolution more efficiently and get more accurate results.

Modified image based energy function

Segmentation using image based energy function with intensity information alone results in poor segmentation as atypical type hepatic hemangiomas are characterized as round-shaped, heterogeneous echo texture tumor on ultrasound images. Thus with the prior knowledge of the shape of the tumor, a local constraint is introduced in the level set method in the form of the initialization of the curve and stopping criterion.

Shape based initialization curve

The robustness of the initial conditions of the curve is an essential parameter for the accurate segmentation of the tumor. The initial shape of the curve along with its size and position determines the way a curve evolves towards the boundary of the tumor. Generally in most of the level set methods, the initial curve is taken as $N \times N$ size square inside or outside the tumor region. The proposed method introduces the shape based statistics of tumor while initializing the curve. This is achieved by measuring the length inside the tumor in X-direction and Y- direction such that the curve lies inside the tumor region. Considering the larger length as major axis and shorter one as minor axis, the curve is initialized as an ellipse.

$$\frac{(x - h)^2}{a^2} + \frac{(y - k)^2}{b^2} = 1 \quad (4.11)$$

where,

a is the semi- major axis, b is the semi- minor axis and (h, k) are the coordinates of the centre of the ellipse.

Shape based stopping criteria

A shape based stopping criteria is introduced to guide the evolving curve towards the boundary of the tumor. By introducing this stopping criterion it is made sure that the curve is converging towards the required local minima. This is achieved by measuring the maximum length of the tumor in X direction and Y direction. These values are then considered as threshold values D1 and D2 respectively as shown in fig. 4.2. Monitoring the maximum length of the evolving curve in X and Y directions, the evolution of the curve is guided towards the boundaries till the required region of the tumor is cover using the threshold values.

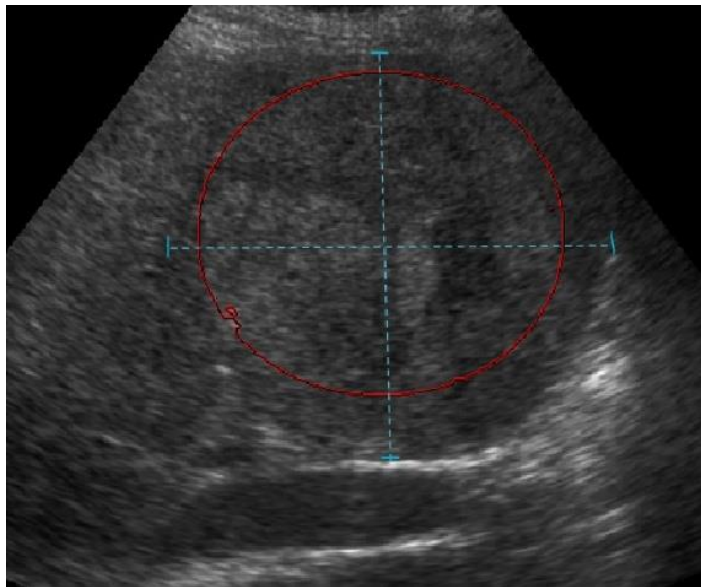


Fig. 4.2- Measurement of maximum length in X and Y direction represented with blue lines as D1 and D2 respectively. Red lines- evolving contour before meeting the stopping criteria.

The steps followed in the proposed segmentation method are given below:

Step 1: Read the de-speckled image J .

Step 2: Measure the maximum length of the tumor in X direction by selecting two seed points at the extreme points of the X- axis and in the similar manner measure the maximum length of the tumor in Y direction.

Step 3: Maximum distance in X- direction is denoted as D1 and that in Y- direction as D2.

Step4: Create an elliptical binary mask that lies inside the tumor region using eq. (21).

Step 5: Signed distance function (SDF), ϕ of this binary mask is computed which is used as the level set function. The curve C is marked as the zero level of ϕ .

Step6: The region which has $\phi > 0$ is the region outside the curve and similarly the region with $\phi < 0$ is the region that lies inside the curve.

Step7: The area inside and outside C is calculated as A_{in} and A_{out} respectively

Step8: Probability Density Function for the region is calculated as R_{in} and for the region outside the curve as R_{out} .

Step9: The image based energy and the regularization term are calculated.

Step 10: The dynamic energy function that helps the curve c to evolve is made by combining the image based energy and the regularization term.

Step 11: The length of the evolving curve in the X direction $d1$, is monitored and so is the length in the Y direction $d2$. When the value of $d1 = D1$ & $d2 = D2$ the evolution of the curve is terminated.

Step12: The curve is reinitialized by reinitializing the signed distance function to its zero level using sussman method to prevent the level set function to become too flat.

4.2.3 Post-Segmentation Processing

The segmented tumor should be superimposed on the original image to analyze the accuracy of the segmentation method. This representation of the tumor is essential as the radiologist can easily see the affected region as it will be highlighted. Diagnoses of the problem become easy and less tedious and time consuming. The steps to be followed are:

Step 1: Read the original ultrasound image, I .

Step 2: Read the segmented image that is obtained after performing the segmentation.

Step3: Compute the boundary of the segmented region.

Step 3: Superimpose the two images such that the segmented boundary is placed exactly over the hemangioma region in the original image.

CHAPTER 5

EXPERIMENTAL SETUP

5.1 Experimental setup for segmentation of hepatic cyst

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 fig. 5.2.

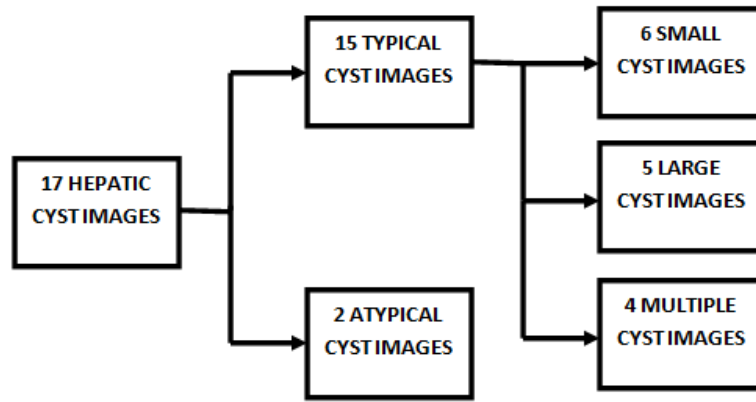


Fig.5.1 Flowchart describing hepatic cyst dataset.

5.2 Experimental setup for segmentation of hepatic hemangioma

A dataset of 50 ultrasound images of benign hepatic tumor is composed for the assessment of the proposed method. The dataset is divided into two categories i.e. clinical and online database as shown in fig 5.2. Clinical dataset was acquired in the time period between March 2008 to May 2009 from the Department of Radio diagnosis, Postgraduate Institute of Medical Education & Research (PGIMER), Chandigarh, India. This dataset consists of 7 typical and 4 atypical ultrasound images. The online available dataset used in the present work is provided by the Hitachi Medical Systems Europe and the Radiology Department of the Gelderse Vallei Hospital in Ede, Netherlands. This dataset consists of 28 typical and 11 atypical benign ultrasound images [42].

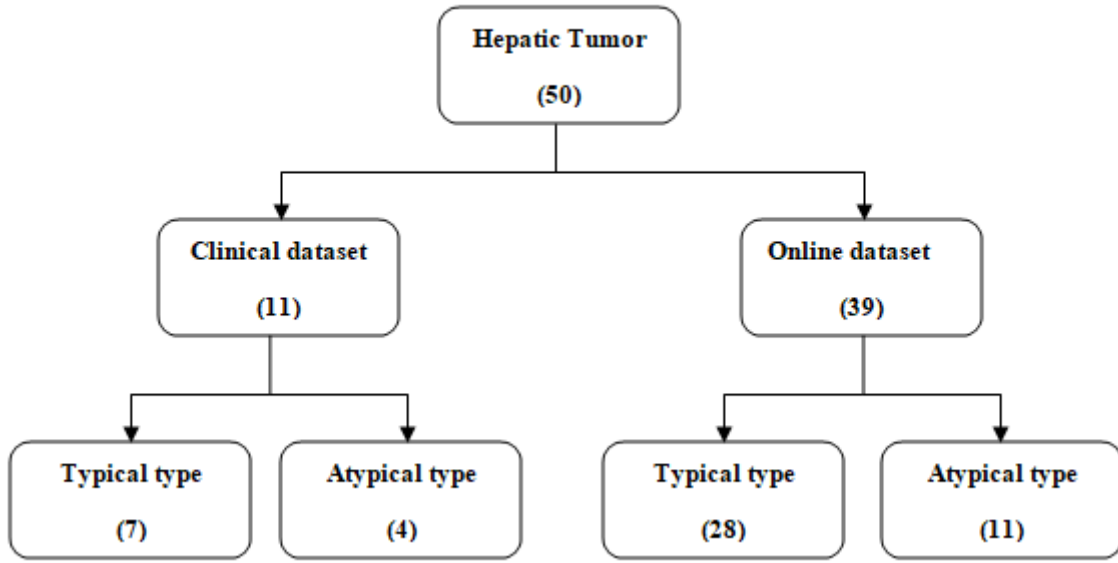


Fig 5.2- Flowchart describing hepatic hemangioma dataset

5.3 Software implementation

The proposed method was implemented using MATLAB[®] R2014a (8.3.0.532) on windows 10. The software was executed on HP laptop with Intel[®] Core™ i3-5005U CPU.

5.4 Evaluation metrics

The performance of the proposed method is quantitatively analyzed and evaluated by using metrics like dice similarity coefficient and relative volume difference. These metrics are often used in medical applications to assess the performance of the segmentation methods of tumor on ultrasound images. Performance metrics are briefly described below:

5.4.1 Dice similarity coefficient (DSC): defines about the overlap of different types of segments.

$$DSC = \frac{2(S_g \cap S_{seg})}{S_g + S_{seg}} \quad (5.1)$$

Where S_g represents the ground truth segmentation and S_{seg} represent the segmentation result of hepatic hemangiomas. This overlap measure is normalized, where 0 value of DSC indicates complete dissimilarity between ground truth segmentation result and proposed method segmentation result and 1 value is for perfect segmentation. Therefore more the value of DSC

approaching to 1 more will be the overlapping between original and processed segmented image.

5.4.2 Relative volume difference (RVD): defines the change between the two segments. In the context of tumor segmentation it is expressed as

$$RVD = \frac{A_{seg} - A_g}{A_g} \quad (5.2)$$

Where A_{seg} is segmentation result area and A_g is ground truth segmentation area result of hepatic tumor. The 0 value of the ratio indicates perfect segmentation as the value of this ratio decreases, so does the perfection of the segmentation with imperfect segmentation when the value becomes 1. It gives an indication of how good segmentation relative to the ground truth image. Negative value of RVD suggests that how much volume of segmentation result is smaller than original volume.

CHAPTER 6

RESULTS AND DISCUSSIONS

6.1 Hepatic cyst segmentation results using modified Chan-Vese method

Semiautomatic segmentation of hepatic cyst was successfully executed by modifying the LSM that was developed by Chan-Vese using Mumford-Shah fitting term. The segmentation results of original method and modified method are compared in this section and there quantitative analysis is also demonstrated. Figure 6.1 shows the comparison between the original and the proposed method. Increased number of pixels which are used to calculate the regularization term improves the segmentation results as shown in fig. 6.1. The regularization term basically checks the intensity variations of the pixel around its neighbourhood. Thus by increasing the number of pixels in the surrounding neighbourhood of the pixel local variations can be monitored more precisely. Thus improvement is achieved as the regularization term will help the curve to evolve considering more specific definitions of the tumor.

Figure 6.1 also demonstrates the pixel count for both the methods as well as the ground truth which was counted under the guidance of the expert. The pixel count also clearly illustrates that by increasing the number of pixels in the neighbourhood for calculating the regularization term improves the segmentation results. For better quantitative analysis of the segmentation results, DSC and the RVD are calculated for both the methods and are shown in the table. The hepatic cyst dataset was further classifies as small cyst, large cyst, multiple cysts and atypical cyst images.

Table 6.1 - Quantitative comparison of the hepatic cyst results

Parameters		Disc Similarity Coefficient (%)		Relative Volume Difference (%)	
		Original Method	Proposed Method	Original Method	Proposed method
Typical	Small cyst	94.9	97.9	37.0	30.3
	Large cyst	91.1	94.1	43.6	36.0
	Multi cyst	95.2	98.2	23.5	19.3
Atypical		93.9	95.7	45.5	34.9

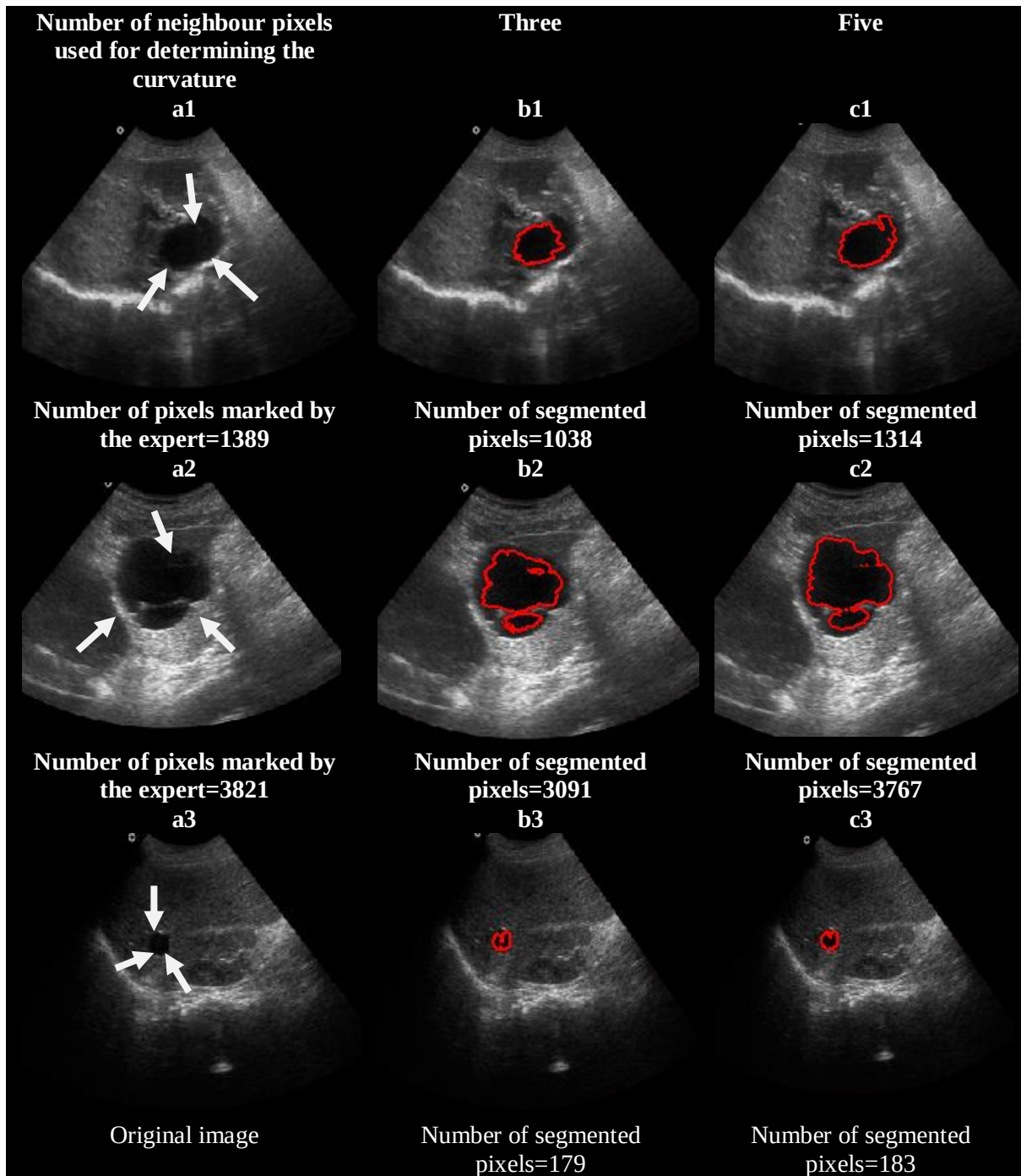


Fig 6.1. -Comparative segmentation results of three, five and seven point central difference method.

The values of DSC as shown in the table 6.1 demonstrate that segmentation results of the proposed method are better than that original Chan-Vese method. Higher the value of DSC, closer the segmentation results are to the ground truth. Similarly the RVD values illustrates that the proposed method is more accurate than the original method. Lower the value of RVD, more accurate is the segmentation method.

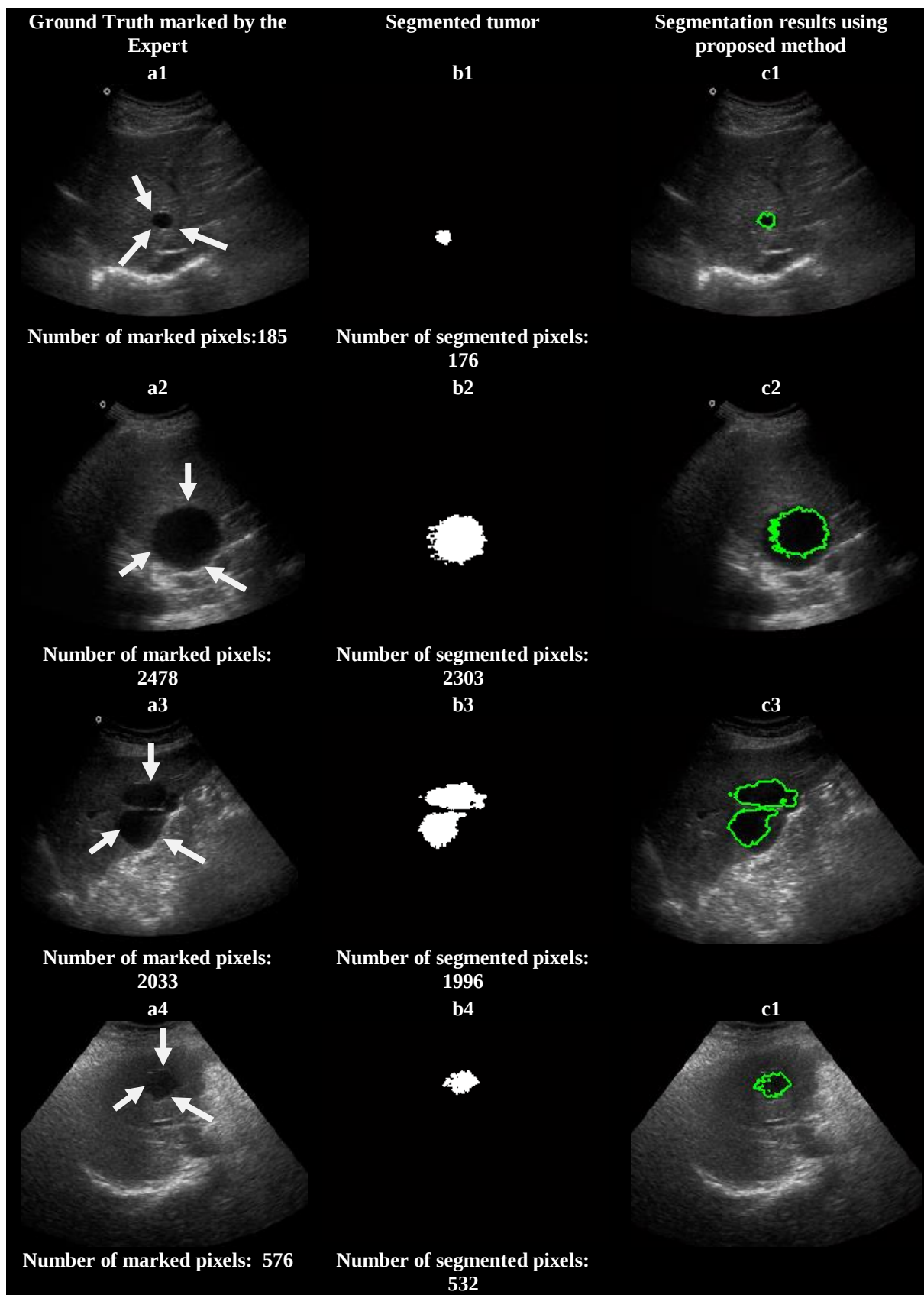


Fig. 6.2 - Steps followed for the tumor segmentation using the proposed method
a1 – a3: Original image with tumor region marked by the expert.
b1 – b3: Tumor area segmented.
c1 – c3: US images with segmented region highlighted.

The segmentation results of the proposed method for all the cases of hepatic cysts are exemplified in fig. Ground truth as shown in fig. 6.2 (a1) - (a4) were marked under the guidance of the expert and then the number of pixels in the marked tumor were calculated. The tumor that was extracted using the proposed method is shown in the fig. 6.2 (b1) – (b4) and fig. 6.2(c1) – (c4) demonstrates the desired segmented tumor region that was obtained using the proposed method marked on the original US image. The dataset was classified into four classes by the expert to check the accuracy and effectiveness of the proposed method by varying the tumor size and intensity homogeneity. These variations in the dataset can also be seen in fig.6.1 where fig. 6.2 (a1) – (c1) illustrates the segmentation steps for US images with small hepatic cysts. Figure 6.2 (a2) – (c2) represents an example for the large hepatic cyst whereas fig.6.2 (a3) – (c3) and fig. 6.2 (a4) – (c4) illustrates segmentation results obtained for multiple cysts and atypical cysts respectively.

6.2 Hepatic hemangioma segmentation results using modified distribution metrics method

6.2.1 Parameters setting

i) Pre- segmentation processing

Proposed method is made effective by reducing the speckle to the extent that the tumor boundary is clearly visible in the de-speckled image. Efficient implementation of the SRAD filter is determined by three parameters, (i) Threshold value, Th that decides the number of iterations (ii) scaling factor and (iii) number of iterations.

The threshold value Th is used to determine the number of iterations required for the desired segmentation results. Empirically, it is observed that segmentation results highly depend upon how accurately the boundary of the tumor is detected. The required accuracy was achieved for most of the cases when the threshold value lies in the range of 50 to 75. The value is fixed to 60 as for this value the segmentation results obtained is closest to the desired segmentation results.

Second parameter that determines the efficiency of the SRAD algorithm is the scaling factor. This parameter controls the amount of smoothing SRAD algorithm will provide to the input image. The value of scaling factor was varied in the range of 0.01 to 0.001 and while performing these experiments it was observed that bigger the value of scaling factor, more

fine details of the image is reduced. To achieve desired definition of the boundary details, the value of scaling factor is fixed as 0.025.

The dataset used in this study is acquired from two different sources, thus there are intensity variations in these dataset. The desired segmentations results are achieved by varying the number of iterations in the range of 150 to 300. It is observed that for the clinical dataset the required results were obtained at the value of 250 whereas for online dataset the number of iterations required for desired results is 200.

ii) Segmentation phase

The desired segmentation results are obtained by performing many experiments to get the optimized value of two parameters i.e. β and Δt .

Value of weighted area term β , which gives extra driving force to the contour, is determined according to the requirement of direction in which the curve evolve. The value of weighted area term was varied in the range of -1 to 1. Empirically, it was observed that negative values of β evolves the curve outwards whereas positive values of β evolves the curve inwards from the initial conditions. It is also observed that small values of β is preferred to avoid leakage of contour at weak edges. After performing many experiments the desired evolution of the curve was obtained for the value of β at 0.05.

The value of time step Δt is selected in such a way to achieve the required convergence. Many experiments were performed and it was observed that if texture is smooth the results will be better with larger value of time steps whereas in the case of irregular texture smaller time steps are required as in the case of the tumours. Thus the value of time step is selected as 0.4 to maintain stable evolution of contour for desired segmentation results.

6.2.2 Segmentation results

The tumor segmentation results of proposed method on all dataset cases are discussed in this section. A qualitative comparison of ground truth marked by expert radiologist and segmented tumor extracted by proposed method is also done in this section.

Case 1: Clinical dataset

Figure 6.3 illustrates the tumor segmentation results on typical ultrasound images achieved using the proposed method. The quantitative comparison of the segmentation results with the ground truth is also demonstrated. The results illustrates that the desired segmentation region is close to the ground truth as the boundary of the segmented region is superimposed on the

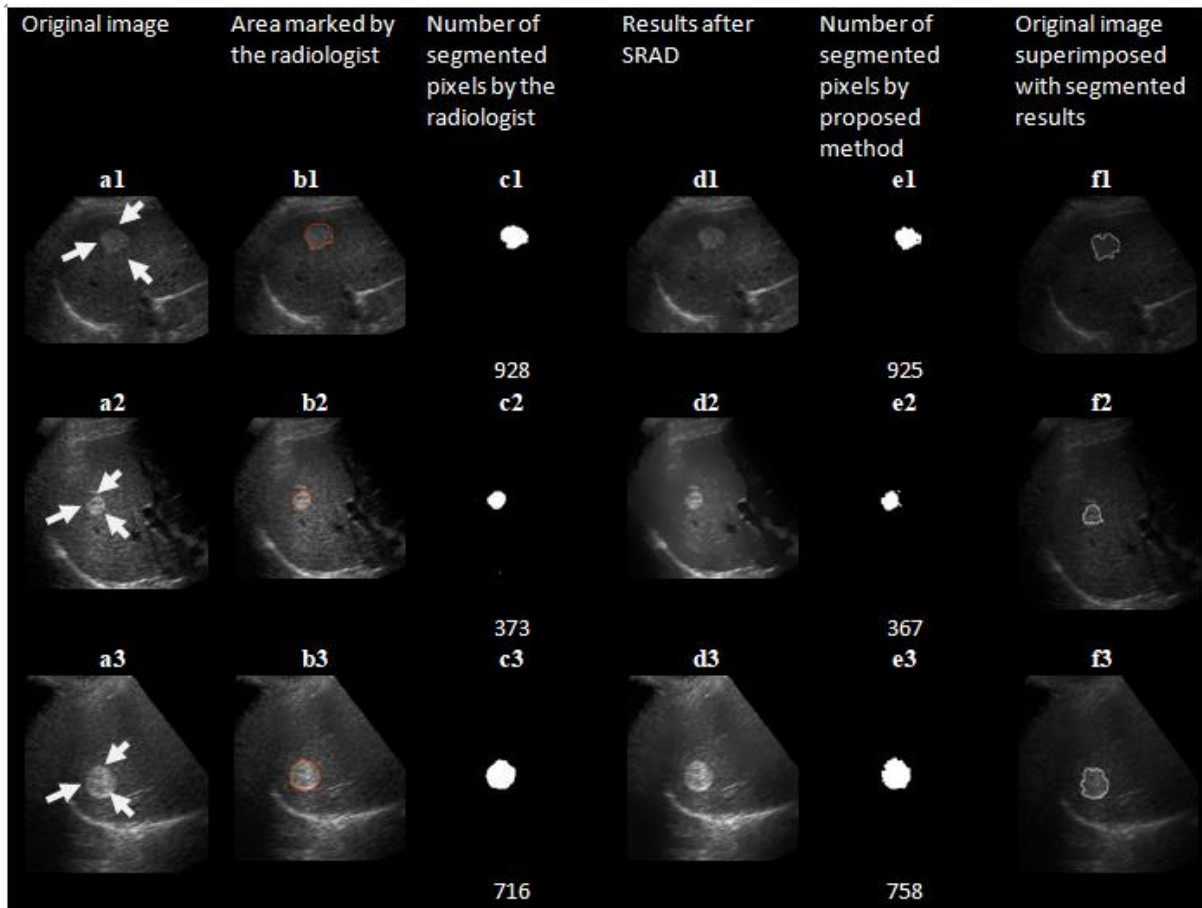


Fig. 6.3- Segmentation results extracted by proposed method on typical clinical dataset.

- a1 – a3: Original image
- b1 – b3: Tumor area marked by the radiologist
- c1 – c3: Ground truth
- d1 – d3: De-speckled image after SRAD is applied.
- e1 – e3: Segmented tumor by proposed method with pixel count.
- f1 – f3: Original image superimposed with segmented results.

original ultrasound images and the boundary is exactly overlapping the boundary of the desired tumor region.

Figure 6.4 represents the tumor segmentation results on atypical type ultrasound images using the proposed method. Segmented results are compared with the ground truth and it can be seen that the required segmentation region is matching with the ground truth as can be seen by the pixel count of the segmented region and the number of pixels on the ground truth. The boundary of the segmented region is superimposed on the original ultrasound images and the boundary is almost overlapping the boundary of the desired tumor region.

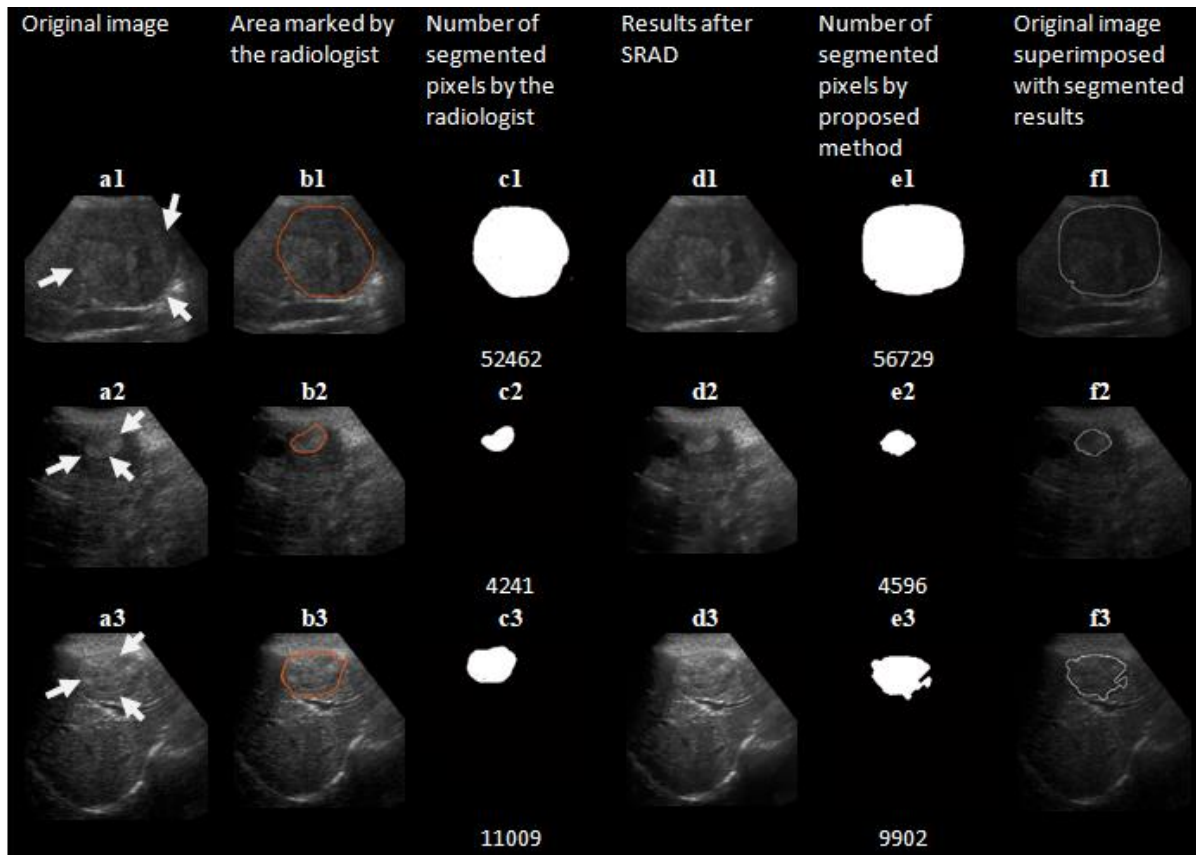


Fig. 6.4 - Segmentation results extracted by proposed method on atypical clinical dataset.

a1 – a3: Original image

b1 – b3: Tumor area marked by the radiologist

c1 – c3: Ground truth

d1 – d3: De-speckled image after SRAD is applied.

e1 – e3: Segmented tumor by proposed method with pixel count.

f1 – f3: Original image superimposed with segmented results.

Case 2: Online dataset

Segmentation results of typical type ultrasound images using the proposed method are illustrated in fig.6.5. The segmentation results of the proposed method are similar to the ground truth and the comparison is illustrated in fig.6.5. The pixel counts quantify the comparison of the two images. The boundary of the segmented region superimposes exactly the boundary of the desired tumor region. Segmentation results of atypical type ultrasound images are depicted in fig.6.6. Accuracy of the results can be seen as these results are compared with the ground truth that was provided along with the images. The pixel count along with superimposed boundary that can be seen in the fig. 6.6 shows the accuracy of the segmentation method qualitatively.

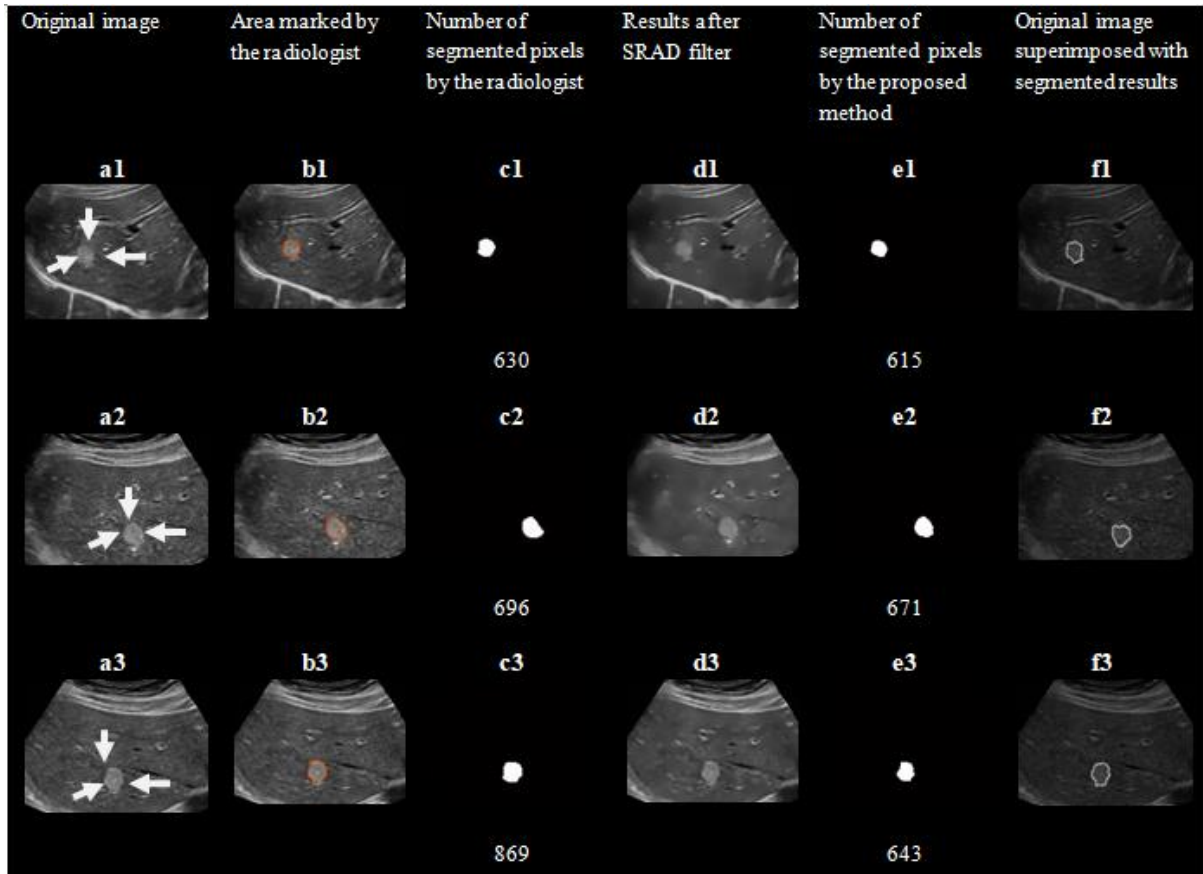


Fig. 6.5- Segmentation results extracted by proposed method on typical online dataset.

- a1 – a3: Original image
- b1 – b3: Tumor area marked by the radiologist
- c1 – c3: Ground truth
- d1 – d3: De-speckled image after SRAD is applied.
- e1 – e3: Segmented tumor by proposed method with pixel count.
- f1 – f3: Original image superimposed with segmented results.

The expert suggested classification the input images into three categories, to analyze the segmentation more precisely. The three categories are high, medium and low based upon the quality of the US images. The experts decided the quality of the US images based upon following parameters the boundary blurring, amount of inhomogeneity in the intensity values and SNR ratio. The segmentation results of the proposed method on these three classes are demonstrated in fig. where one can clearly see the affect of the quality of the images on the segmentation results. White line represents the ground truth region marked by the expert and the red line illustrates the segmented results obtained from the proposed method. Figure 6.7 (a1) – (a3) are the examples of the images with high quality. The high quality images exhibits sharp edges for entire tumor with regular boundaries. Thus the segmented region almost covers the entire tumor area marked by the expert. Medium quality class of the US images correspond to the images with blurred boundaries with low value of SNR. The segmentation

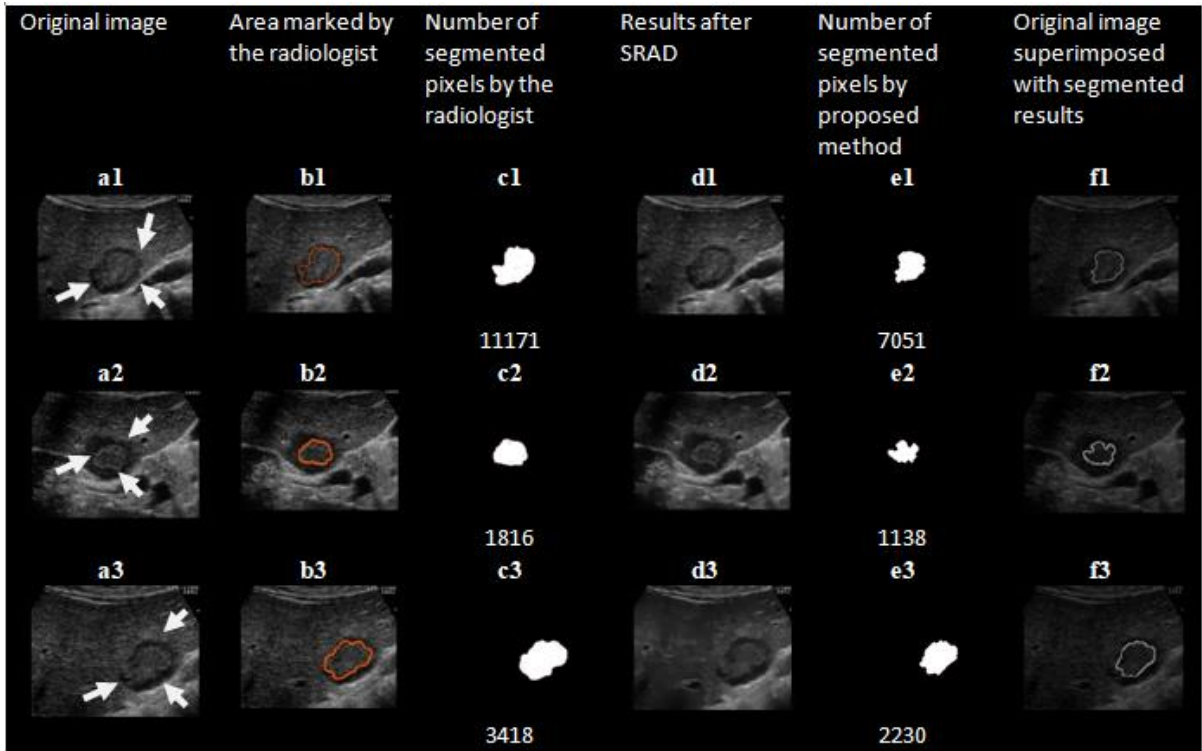


Fig. 6.6- Segmentation results extracted by proposed method on atypical online dataset.

a1 – a3: Original image

b1 – b3: Tumor area marked by the radiologist

c1 – c3: Ground truth

d1 – d3: De-speckled image after SRAD is applied.

e1 – e3: Segmented tumor by proposed method with pixel count.

f1 – f3: Original image superimposed with segmented results

results obtained on these images are shown in fig. 6.7 (b1) – (b3). These results state that although due to blurred boundaries there is a leakage of the curve at the boundaries of the tumor but the segmented region is close to the marked region. An US image is classified as low quality image if it is characterized by extremely inhomogeneous tumor regions. Segmentation results extracted using the proposed method on low quality of US images are shown in fig. 6.7 (c1) – (c3), where it can be seen that the segmented region is not covering the entire marked region but still most of the region is covered.

This experiment that was conducted based upon the quality of the US images is also analyzed quantitatively by calculating the DCS and RVD for all three classes as shown in table 6.2. The value of DCS is maximum for high quality images where as minimum for low quality images. The value of RVD is lowest for high quality images showing high accuracy and the value is highest for low quality images. The variations in the value of DCS and RVD can be seen graphically in fig.6.8 the blue bar in the fig represent DCS and the red bar the RVD values.

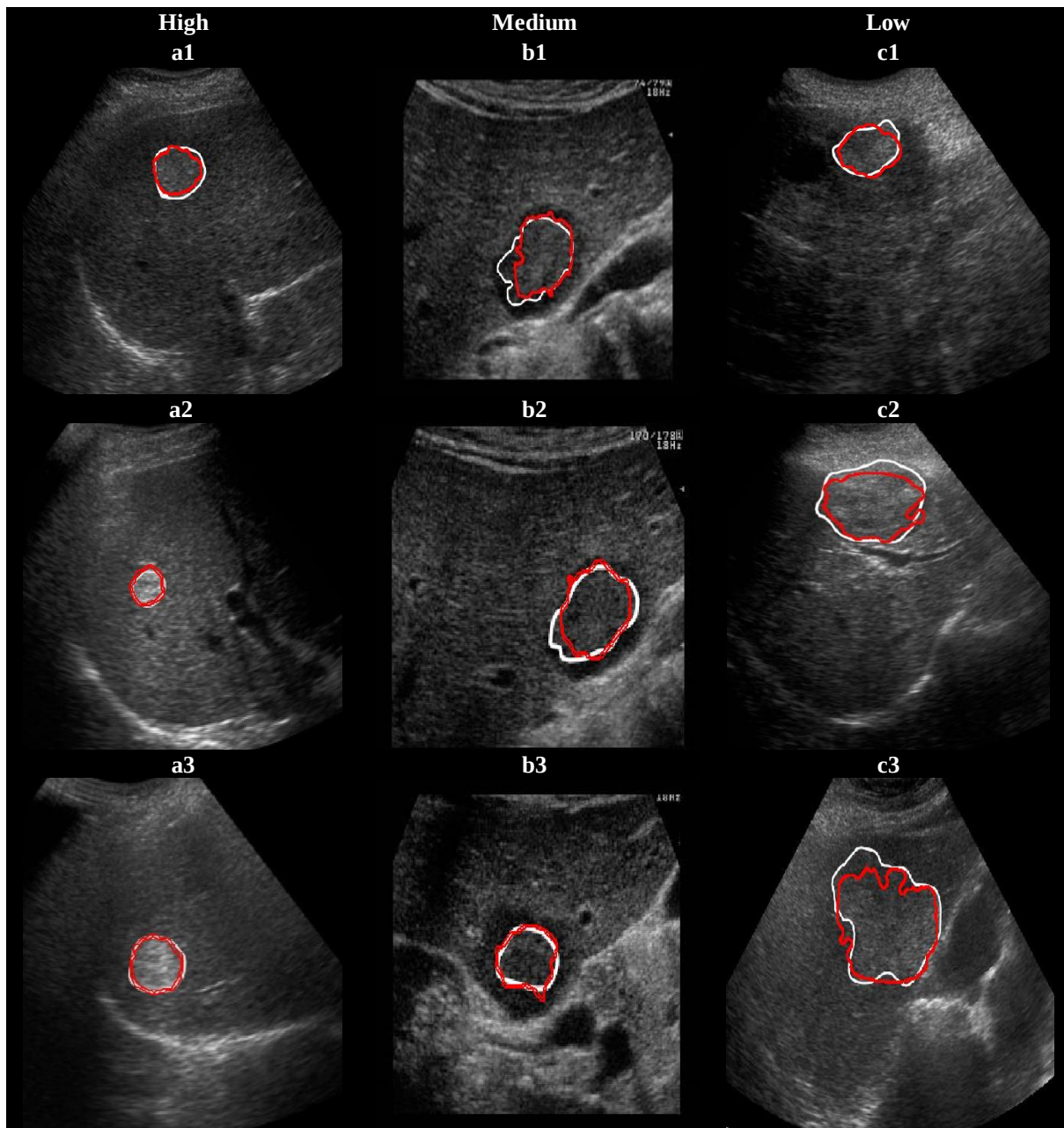


Fig. 6.7 – Segmentation results for hepatic hemangioma using proposed method where the white lines show the tumor region marked by the expert and the red lines shows the segmented tumor using the proposed method.

a1 – a3: High quality US images

b1 – b3: Medium quality US images

c1 – c3: Low quality US images

6.2.3 Comparison of segmentation results

Further validation of the proposed method is done by comparing it with other segmentation methods such as Iterative- FCM method [24], Region difference filter [21] method and modified Chan Vese method [43] which is shown in fig. 6.9.

Table 6.2 – Quantitative evaluation of the proposed method in high, medium and low quality group

	High		Medium		Low	
	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV
DCS	0.95	0.01	0.90	0.02	0.87	0.01
RVD	0.13	0.03	0.16	0.01	0.20	0.02

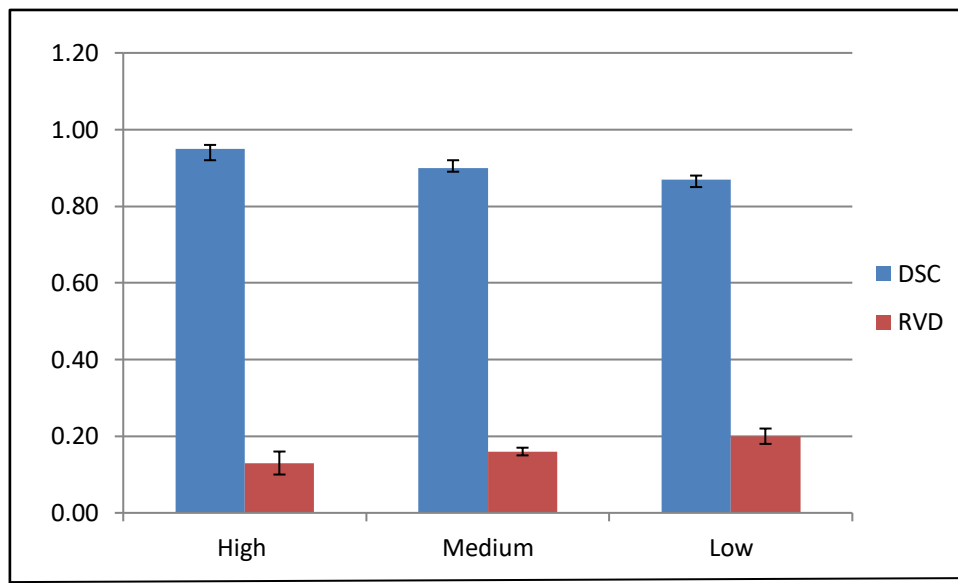


Fig. 6.8 – Bar plots of DCS and RVD measurements of proposed method for high, medium and low groups.

The figure visually illustrates how the segmentation results of the proposed method are better than the other methods. All other methods under-segment or over-segment the tumor as they do not consider the exact boundary details. Figure 6.9(a)-(c) represents the original ultrasound images on which the tumor is marked. The segmentation results of Iterative FCM method are shown in fig. 6.9 (d)-(f) and it can be seen that the tumor is highly under segmented by this method as it roughly detects the tumor boundary. Whereas, the segmentation results of Region difference method and Modified Chan-Vese method are shown in fig 6.9(g)-(i) and fig. 6.9 (j)-(l) respectively. The tumor is over segmented thus the definitions of the boundaries are not that clear. The modification proposed in the present work keep in account those details and improves the results which can be seen in fig. 6.9(m)-

(o). A similar comparison with other methods for the typical type online dataset is shown in fig. 6.10.

Comparison of atypical type dataset cannot be done as other segmentation methods are incompetent in performing the segmentation on such type of images. Thus, the proposed method outperforms other methods.

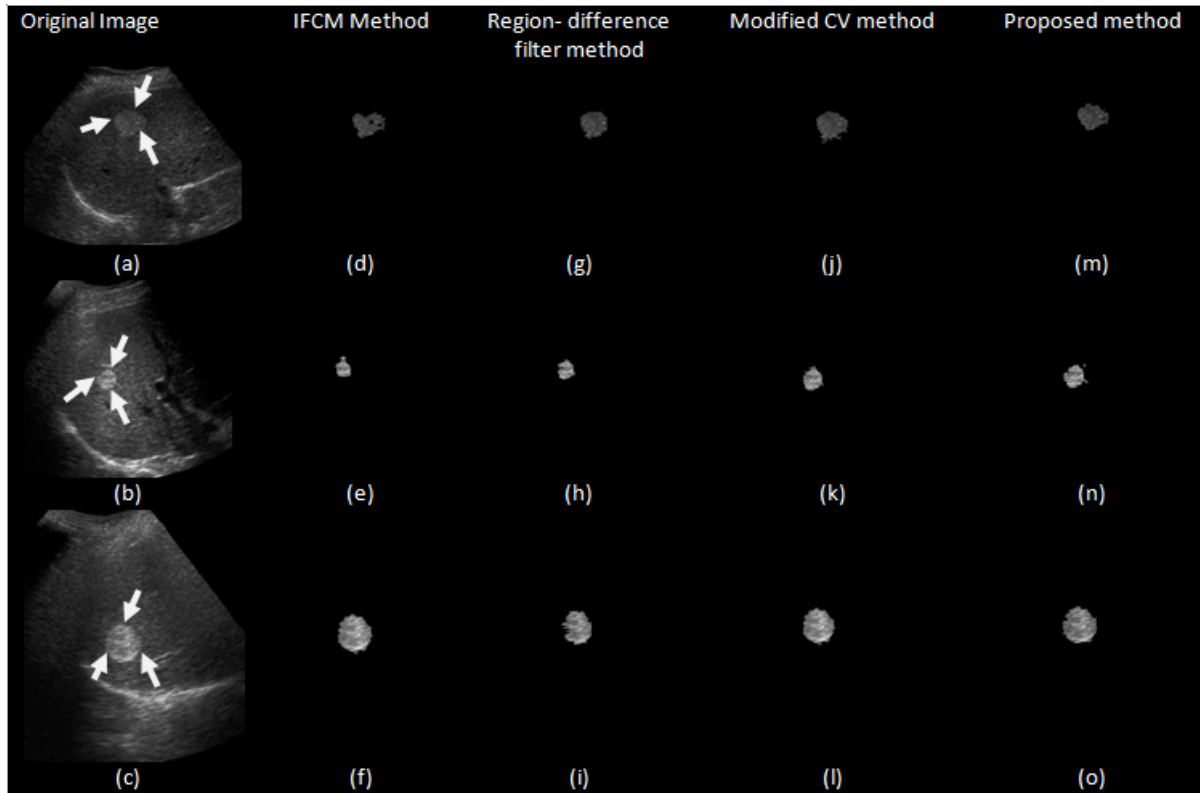


Fig. 6.9- Segmentation results of typical type hemangioma compared with other methods.

(a)-(c) : Original image showing the hemangioma region.

(d)-(f) :Results of IFCM method.

(g)-(i) :Results of Region-difference filter method.

(j)-(l) : Results of Modified Chan-Vese Method.

(m)- (o) :Results of the proposed method

6.2.4 Performance Evaluation

The quantitative evaluation of the proposed method is done with two parameters DSC and RVD. These performance metrics were calculated by comparing the segmentation results of the methods with that of the reference ground truth images marked by the radiologist. Table 6.3 shows the quantitative comparison of all segmentation methods based upon the values of

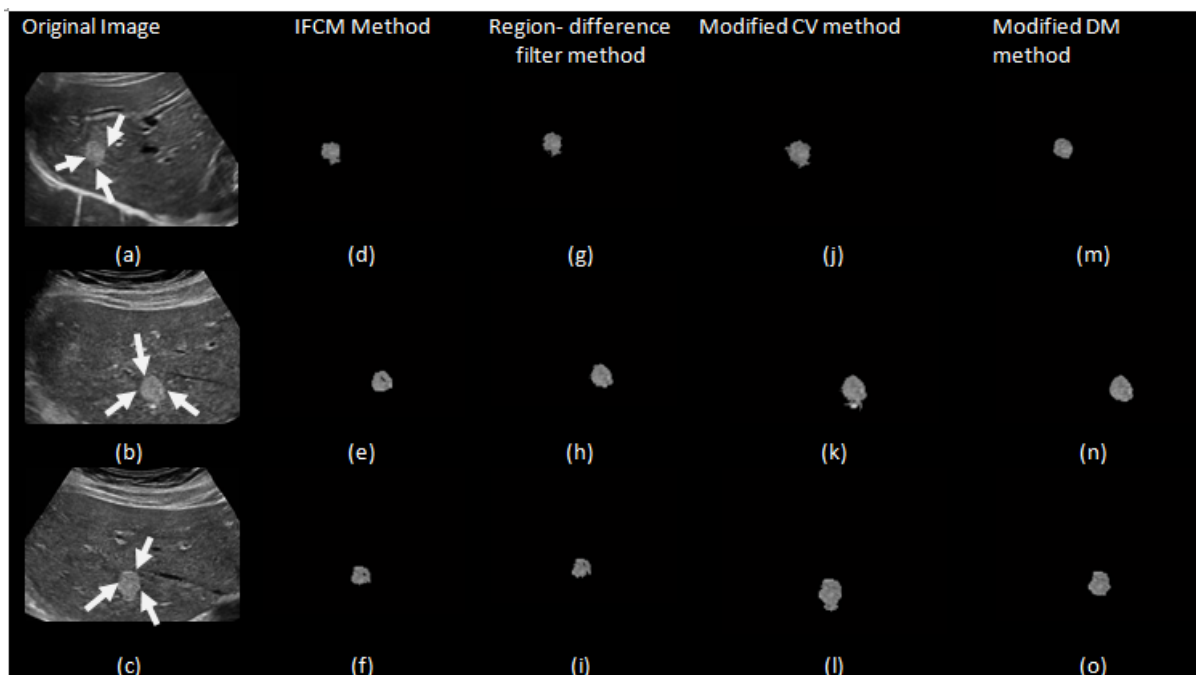


Fig. 6.10- Segmentation results of typical type hemangioma compared with other methods.

- (a)-(c) : Original image showing the hemangioma region.
- (d)-(f) :Results of IFCM method.
- (g)-(i) :Results of Region-difference filter method.
- (j)-(l) : Results of Modified Chan-Vese Method.
- (m)-(o) :Results of the proposed method

DSC. The performance of the proposed method outperforms other segmentation methods for clinical as well as the online typical type database in the terms of DCS, as higher the value of DCS better is the segmentation. The value obtained is perfect 1 for both clinical type and online dataset respectively. The variations in the values of DCS for all segmentation methods can also be seen with help of a bar plot seen in fig. 6.11 (a) and fig. 6.11 (b) for clinical and online typical dataset respectively.

The segmentation methods are also analyzed in terms of RVD as depicted in table 6.4. Accuracy of the methods can be predicted in terms of RVD as smaller is the value of RDV for a method, better is its accuracy. The values calculated for the proposed method for clinical and online typical type images are 0.22 ± 0.01 and 0.19 ± 0.02 respectively. Figure 6.11(a) and fig. 6.11 (b) demonstrate graphically how the proposed method outperforms the other methods in terms of RVD.

The time complexity of an algorithm is defined as time that algorithm takes to execute, which depends upon number of loops or sub-loops present in it. More the number of loops in an algorithm more is the time complexity and thus less the algorithm is unsuitable for the segmentation purpose.

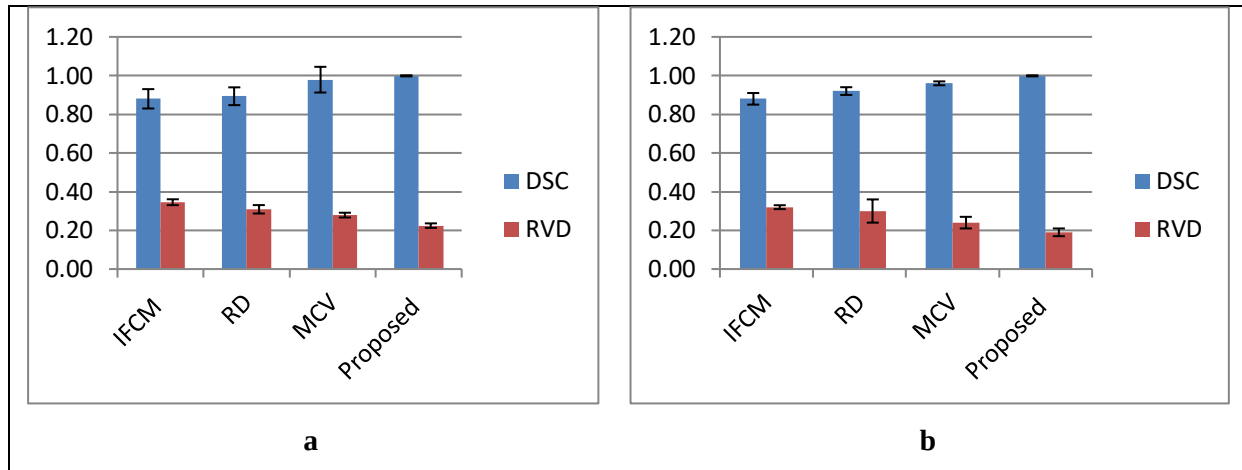


Fig .6.11- Bar plots for DSC and RVD measurements for: (a) clinical dataset (b) online dataset

Table6.4 - The mean and standard deviation values of DCS and RVD for online dataset

	IFCM Method		Region-difference method		Modified Chan-Vese method		Proposed method	
	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV
DCS	0.89	0.03	0.92	0.02	0.96	0.01	1	0.00
RVD	0.32	0.01	0.30	0.06	0.24	0.03	0.19	0.02

A segmentation algorithm is considered more suitable if it takes less time to process and has faster execution i.e. less time complexity. Table 6.5 shows the time complexity of all four segmentation methods and it can be clearly seen that Modified Chan-Vese method has least time complexity. Since, it does not perform well on images with intensity inhomogeneity, it cannot be considered best among all. Space complexity of an algorithm is its ability to replace a file in the same location whenever the file needs to be saved again n again. When a copy of the algorithm is made after saving, it uses more space and thus the space complexity is higher. According to the analysis shown in table 6.5, the

Table 6.5- Comparison of four segmentation on the basis of time and space complexity

Method used	Time complexity (sec)	Space complexity
IFCM Method	$O(n^3/N^{3.4})$	$O(N)$
Region-difference Method	$O(M^3.1/N^{2.1})$	$O(N^2)$
Modified Chan-Vese Method	$O(n)$	$O(N+M)$
Proposed Method	$O(n^{2.1}/M^{1.1})$	$O(N+M)$
Where : $N \times M$ = size of the image, n =number of pixels		

algorithm with minimum space complexity is IFCM method. After performing both time and space complexity, it can be stated that the proposed method which has high space complexity but lower time complexity compared to IFCM method and Region-difference Method is suitable for segmentation purpose. Although it uses more space than these two segmentation methods but till will always perform better and faster.

CHAPTER 7

CONCLUSION

New segmentation methods are proposed and analyzed in this work by modifying two level set techniques. The proposed methods accurately segment the benign hepatic tumor region on ultrasound images. Segmentation on ultrasound images is challenging due to presence of speckle. The fine boundary definitions of the tumor on ultrasound images are preserved by reducing the speckle with the help of SRAD filter. The performance of the proposed method has been validated on database composing of 67 ultrasound images, which are divided into two subsets. First subset contains 17 hepatic cyst images which are subdivided into 15 typical and 2 atypical cystic ultrasound images. The second subset contains 50 hepatic hemangioma ultrasound images. The segmentation of hepatic cyst is done using modified Chan-Vese method, and by introducing the modifications, the proposed method outperforms the original method by 8.92 % in terms of DSC and 27.31% in terms of RVD. As there is intratumoral intensity inhomogeneity in the case of hepatic hemangioma, variations in the probability distribution of the intensity value is used to formulate the images based energy instead of directly using intensity values. The results of proposed methods for typical type hemangioma are compared with other segmentation methods to check the accuracy of this method. The other methods used for comparison are IFCM method, Region-difference filter method and Modified Chan-Vese method. The segmentation results for both datasets using all four the methods are compare qualitatively as well as quantitatively. For the proposed method, the value of DSC obtained is 0.9986 for clinically acquired images and 0.9990 for online available database, whereas the RVD value is 0.2245 for clinically acquired dataset and 0.1993 for online dataset. The segmentation results obtained ob atypical type hemangioma ultrasound images cannot be compared with other methods as they are incapable of segmenting this type of tumor. The proposed method thus outperforms other segmentation methods as it can accurately segment the atypical tumor using the shape based stopping criteria. Thus it can be concluded that to check the rare complications associated with the hemangioma, the size of the benign tumor can be monitored using the proposed method which is more reliable and accurate.

For future development in segmentation method, the major emphasis will be given on automating the segmentation method which can work on ultrasound images with better tumor segmentation accuracy on heterogeneous tumors. By automating the initialization of the curve, computational time will be reduced and user interaction and the segmentation will become more accurate as there will be less chances of inter and intra-user variability.

LIST OF PUBLICATIONS

- [1] I. Kapoor, D. Mittal. “An Efficient Method for Hepatic Cyst Segmentation on Ultrasound Images”, Journal of Biomedical Engineering and Medical Imaging, vol. 3, no.6, pp. 55, 2017

- [2] I. Kapoor, D. Mittal. “A Modified Local Window Level Set Method for Segmentation of Benign Hepatic Tumor on Ultrasound Images”, communicated in the journal of *Ultrasonic Imaging*.

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