MODIFIED DISTANCE REGULARIZED LEVEL SET METHOD TO SEGMENT HEPATIC TUMOR

A Dissertation submitted in fulfillment of the requirements for the Degree
of

MASTER OF ENGINEERING
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Submitted by

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DECLARATION

I hereby certify that the work which is presented in dissertation entitled, "**Modified distance regularized level set method to segment hepatic tumor**", in partial fulfillment of the requirements for the award of the degree of Master of Engineering in Electronic Instrumentation and Control, submitted to Electrical & Instrumentation Engineering Department of Thapar University, Patiala is as authentic record of my own work carried under the supervision of Dr. Deepti Mittal. It refers others researcher's work which are duly listed in the reference section. The matter contained in this dissertation has not been submitted, neither in part nor in full to any other degree to any other university or institute except as reported in text and references.

Place: Patiala

Date: 14-07-2016

(Ritambhara)

This is to certify that the above statement made by the candidate is correct and true to the best of my knowledge and belief.

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NOMENCLATURE

3D-Three-Dimensional

CT-Computed Tomography

LSF-Level Set Function

DRLSE-Distance Regularized Level Set Method

MDRLSE- Modified Distance Regularized Level Set Method

2D-Two-Dimensional

DSC-Dice Similarity Coefficient

RVD-Relative Volume Difference

CAD-Computer Aided Diagnose

HCC- Heptocellularcarcinoma

NECT- Non Enhanced Computed Tomography

GVF-Gradient Vector Flow

AOE-Average overlap error

AVD -Average volume difference

VOE -Volume overlapping error

ASD-Average surface distance

MSD-Maximum surface distance

SI -Similarity index

FPE- False positive error

FNE-False negative error

CLAHE- Contrast-Limited Adaptive Histogram Equalization

ABSTRACT

Severity of liver disease assessment, surgical planning and follow-up of liver cancer treatment essentially require an accurate segmentation of tumor region. However, Intratumoral heterogeneity and minor variations in tumor tissue intensities with respect to surrounding liver tissues are the major challenges in computerized hepatic tumor segmentation and reconstruction of its three-dimensional (3D) volume using computed tomography (CT) images. Level set method is an efficient segmentation method to segment hepatic tumor with the advantage of its ability to (i) model complex shapes of tumor even no prior information about the topology available (ii) split and merge efficiently to represent tumor region. Conventional level set methods face the problem of irregularities during the evolution of level set function (LSF) which leads to distortion of stability and numerical errors. To overcome these problems, curve is stopped and reshaping of degraded LSF is done after fixed interval of time termed as reinitialization. But it is unpredictable that when and how it is to be applied on LSF.A number of modifications was done in recent years for better convergence and to handle the problem of reinitialization in conventional level set methods. One approach was introduced by Li *et al.* to eliminate the need of reinitialization by introducing double well potential term for regularization and they used edge-based energy functional to converge or stop the contour at the boundary of interfaces having distinct intensity characteristics. However it faces the problem of oversegmentation or boundary leakage during the evolution of LSF. In the present work, a new method has been proposed to significantly overcome the boundary problem encountered during implementation of upwind scheme inspite of central difference scheme used in DRLSE method in external energy function to stop the contour to converge at exact boundary of the tumor. Further, the present work proposed modifications in the template of upwind scheme to capture accurate definition of tumor boundary using higher number of neighborhood pixels. This way the proposed method avoids the problem of leakage during the segmentation of boundary. The results of

modified DRLSE method clearly demonstrate that the proposed method outperforms the DRLSE method in terms of Dice similarity coefficient and Relative volume difference. Further, Tumor volumetry has become an essential surgical tool to know the extent of liver cancer and staging, guidance during surgery and follow-up the treatment. Thus, 3D volume is constructed using segmented two-dimensional (2D) slices and this structure can demonstrate the extent of tumor and its volume for further treatment and planning using CT image slices.

CHAPTER 1
INTRODUCTION

1.1 Overview

Liver is a vital organ in the body that continuously filters the blood in the body for detoxification. Due to this, liver is frequently accessible to cancer cells traveling in the bloodstream. Computed tomography(CT) is the screening test preferred by doctors to estimate the extent of cancer in the body. It is used to assess whether the disease is responding to treatment and to accurately guide cancer treatment during a procedure. The segmentation of liver diseases is not straightforward because liver and tumors have high variability in both shape and intensity values with very small observable changes between healthy liver tissues and tumors. Hepatic tumor segmentation mainly faces following difficulties

i) Low contrast tumors with surrounding hepatic tissues.

ii) Convex nature of tumors.

iii) Intratumoral heterogeneity.

The presence of blood vessels and calcification of tumors increase the complexity of tumor segmentation. Therefore an efficient and more accurate segmentation algorithm is needed for tumor boundary extraction. The interpretation of CT images may be different by the different radiologists because of their own search pattern and experience. Furthermore, the images may be noisy with low contrast. Therefore there is a need to provide a computer aided diagnose (CAD). Despite many advances in development of liver segmentation methods, it is still very difficult to apply them practically. That is the reason of development of various automatic and semiautomatic methods which may reduce the mental work of human and may provide accurate delineation of the area of interest. Therefore a huge research work is going on in this direction. The segmentation of liver is different because of inter-organ intensity resemblance of liver with their nearby organs and also liver show intra organ variation too in Abdomen CT images. Active contour method and level set methods has been widely used in segmentation of liver and tumor due to their inherent capability to segment the liver portion from abdomen CT images. Comparative study of both methods has been done because they are very similar in context of their principle and working. In the present study, a comparative study of active contour and level set method is done to segment liver portion from abdomen CT images and a segmentation algorithm is tried to develop which can segment different types of tumors with less human interaction.

1.2 Main contribution:

In the present work, segmentation of liver and tumor is done for efficient liver and liver tumor extraction. Firstly, active contour or snakes and level set methods are implemented to segment liver portion from abdomen CT images. Both methods are tested on 52 liver images collected from Max Saket hospital Delhi, India. For tumor segmentation, distance regularized level set evolution method is modified to overcome the drawback of boundary leakage which leads to over segmentation in case of weak boundaries tumors. Modification in Distance regularized level set method (DRLSE) method is done by applying templates of large size neighborhood pixels in the upwind scheme in place of central difference scheme employed in DRLSE to approximate spatial derivative. This in turn applied to calculate the gradient term of edge indicator function for better segmentation. Qualitative analysis of modified method is done by comparing ground truth images marked by expert radiologist with segmented output of level set method. DRLSE method was tested on liver tumor images. The proposed method was tested on 3 datasets different types of tumors i.e. homogenous(hypointense type) tumors and heterogeneous type of tumors with mixed tissue intensities collected from Max Saket hospital Delhi, India and Mahajan Imaging Centre at BLK super specialty hospital, Delhi, India. Furthermore, 3D volume reconstruction is done to extract exact volume of hepatic tumor. By the choice of different templates the accuracy of tumor segmentation is increased considerably and it can be employed for the diagnosis of different cases of tumor in the liver. It can be seen clearly by the results of experiments that this modified level set method is more robust to segment hepatic tumor. Tumor volumetry helps in better visualization and assessment of hepatic tumor.

1.3 Thesis overview

In the present work, snakes or active contour and level set method is used to segment liver form abdomen CT images and distance regularized level set method has been modified to improve edge detection by modifying the edge indicator function for tumor segmentation. Both methods are illustrated and validated by evaluating its performance on different CT datasets. Thesis is organized by giving overview and main contribution of thesis work in Chapter 1. In chapter 2 background of liver, liver cancer, Computed tomography are discussed followed by related work in the area of liver and tumor segmentation is given in Chapter 3. Active contour method and level set method is described in Chapter 4 followed by motivation behind the improvement of level set method and Modified distance regularized level set evolution method for tumor segmentation is described in Chapter 5. Patient dataset information and evaluation metrics used to evaluate the accuracy of proposed method is discussed in Chapter 6. Results obtained using Active contour and level set method of liver segmentation, modified distance regularized level set method(MDRLSE) method for tumor segmentation and its related discussion is summarized in Chapter 7. In the end, the whole work, future scope and an improvement in level set method is concluded in Chapter 8.

CHAPTER 2
BACKGROUND AND SIGNIFICANCE

2.1 Liver cancer:

According to American cancer society, liver cancer is the third most common cause of cancer-related deaths with the sixth highest incidence worldwide accounting for more than six million people deaths and seven million incidences [1]. Liver is the largest gland in the body which constantly filters blood, process nutrients and remove toxins from the body that makes it an easy target for cancer cells travelling through blood cells. Tumors are the abnormal growth of tissues that may be categorized as malignant (cancerous) or benign (non-cancerous) tumors. Malignant tumors are further sub-categorized as primary and secondary liver cancer (Metastasis).

2.1.1 Types of Liver cancer:

1) Primary liver cancer.
2) Secondary liver cancer.

1) Primary liver cancer: It is the cancer which develops with in liver and is sixth common cancer worldwide with second leading cause of cancer death.

in its early stages when it is most treatable whereas secondary liver cancer is very hard to treat because it has already spread [4].

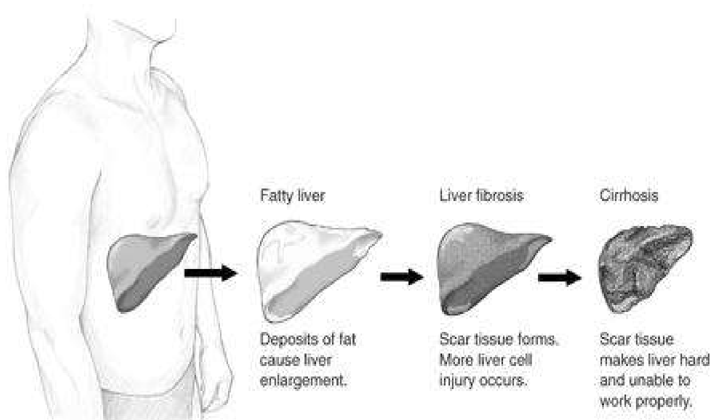


Fig.1 Stages of liver cancer.

It includes **Hepatocellular carcinoma (HCC**) and **Cholangiocarcinoma.** The primary liver cancer has their origins in fatty liver disease and alcohol-associated cirrhosis. Fatty liver disease is the initial stage of liver damage in which the size of liver increase from its normal size. This enlargement of liver is caused due to deposition of fat on the liver [2]. Whereas, the last stage of liver damage where damage of liver cause liver cancer is Cirrhosis in which the size of liver becomes smaller than its normal size due to irreversible scarring of liver [3].

2) Secondary liver cancer or Metastases: Liver metastases are hepatic cancers that spread from other parts of the body. The liver is a major candidate for metastases form cancers from other parts of body. It is twenty times more frequent than primary liver cancer.

The long-term survival of patient suffering from liver cancer is highly dependent on the early detection and identification of type of liver tumor because primary liver cancer is treatable only These different stages of liver disease cannot be diagnosed in their early stages because most of the liver disease does not show any major symptoms in the beginning. Therefore, the 3D volume reconstruction of 2D liver CT image slices can play a major role for the detection of liver disease (in the later cancer stage) stages.

2.2 Computed Tomography (CT):

The diagnose of liver cancer/disease is performed using invasive and noninvasive methods like biopsy and computed tomography(CT) and magnetic resonance imaging(MRI) respectively. CT is highly preferable imaging technique because it gives good contrast as compared to ultrasound and is more cost and time efficient than MRI. Computed tomography is the screening test preferred by doctors to estimate the extent of cancer in the body. It is used to assess whether the disease is responding to treatment and to accurately guide cancer treatment during a procedure. These imaging tests are suggested by the doctor for the

i) Detection of suspicious area inside the liver
ii) Identification of tumor i.e. it is cancerous or non-cancerous
iii) Staging of liver cancer.

A CT can identify and provide precise information about the size, shape, and position of any tumor. 2D cross-sectional slices of abdomen are obtained using CT and after that, 2D slices are stacked to form tumor volumetry. Tumor volumetry is becoming an essential surgical tool to

(i) Know the extent of liver cancer and staging (volume increases in case of fatty liver disease and decrease in case of cirrhosis which are first and last stages of liver cancer respectively) before tumor resection.
(ii) Provide the guidance during surgery.

(iii) Follow-up the treatment after tumor resection and for further treatment planning.

The variation in gray values of hepatic tumor is due to the type of tumor, timing and extent of injection of contrast agent in the liver. In non-enhanced CT (NECT) images, hepatic tumors are not visible because the intensity difference between tumor tissue and nearby hepatic tissues is very low [5, 6]. In NECT images, only very few tumors which consist of fat, hemorrhage can be accurately detected. Therefore, multiphase contrast enhanced images are recommended. Blood vessels in the liver do not supply this contrast agent equally. In parenchyma, blood is supplied through portal vein so it enhances in the portal venous phase but all types of tumors get their supply from hepatic artery, so they usually enhance in arterial phase (starting phase of injection of contrast agent to liver). So hyper vascular (brighter than background liver) tumors get enhanced in arterial phase and hypo vascular (darker than background liver) tumors which are mostly metastases get enhanced in portal venous phase. Best images of tumors are obtained in equilibrium phase. Therefore, multiphase contrast enhanced images give different patterns and contrast of tumors. This intensity distribution inside tumor can be uniform and non-uniform i.e. homogenous (uniform distribution) and heterogeneous (non-uniform distribution) tumors as shown in fig.1. Further tumors are divided into different categories in accordance with intensity and texture characteristics of tumor are as follows

(A) (B) (C)

Fig.2.2 Three different types of complex tumor for segmentation (A) Homogeneous tumor (B) Highly heterogeneous tumor with mixed tissue density (C) Multiple tumors with some heterogeneity. Area marked with red lines: Tumor area in liver.

- Homogenous tumors which have uniform intensity divided into two subcategories-hyper dense (brighter than background) and hypodense (darker than background) tumors.
- Heterogeneous tumors with mixed tissue intensity.
- Multiple tumors with some heterogeneity.

CHAPTER 3
LITERATURE REVIEW

3.1 Liver segmentation using snakes and level set method

In recent years, several segmentation methods have been introduced to segment liver that is based on intensity, region and other features of the image. The accuracy and implementation of these methods can be accessed on the basis of these cases that is Abdomen CT images with i)low contrast ii)Inhomogeneous distribution within liver iii) convexity of liver iv) automatic/semiautomatic implementation of CAD.

[7] S.J. Lim *et al*. proposed a method in which they used adaptive thresholding, iterative morphological filtering technique for pre-processing and contour based approach for segmentation. They divide CT image into 64x64 pixels to reduce computation time. Area is calculated which achieve an accuracy of 96% in contrast enhanced images. They only work on contrast enhanced images so this method cannot be applied to low contrast and inhomogeneous images because threshold values will be different for different regions in inhomogeneous Ct images.

[8] Massoptier and Casciaro introduced a method in which they used mean shift filter in preprocessing step filter is designed in which pre-processing time reduction and edges are preserved and segmentation is performed by active contour method using gradient vector flow. This method is applicable only on homogenous images and misclassification occurred due to same intensity variation of liver and heart.

[9] Massieh et al. used mean shift filter in preprocessing. The biggest achievement of their method is the application of method in non contrast enhanced images. There is no pre-assumption about shape and intensity range the limitation of the method was leakage in cases where liver contour is not clear due to homogeneity.

[10] Casciaro *et al*. developed an adaptive initialization method to produce fully automatic processing frameworks based on graph-cut and gradient flow active contour algorithms. Mean shift filter with 64 squared regions are employed for initialization. This makes initialization

automatic because only that portion is included where standard deviation is less than 1%. Graph-cut algorithm and active contour gradient vector flow achieve mean DSC =95.49% and 96.17% respectively. In their implementation, active contour algorithm encounters a problem with tumor positioned just under the liver surface. These structures have different intensity values as compared to liver. Therefore they are initialized outside the liver. Previous research work related to segmentation of liver is shown in table 2.1.

Table 2.1: Previous research work related to segmentation of liver :

Author	**Year**	**Data-set**	**Approach of segmentation**	**Image processing techniques(pre -processing)**	**Image processing techniques(segmentation)**	**Parameter**
Seong-Jae Lim *et al*.	2005	10	Semi-automatic	1)Thresholding 2)Morphological filtering 3)k-means clustering	Contour based segmentation	Area and volume Average correctness=96%
Massoptier and Casciaro	2008	21	Automatic	1)Mean shift filter 2)Stastical model descrimination of liver(64 squared regions) 3)Morphological functions	Active contour technique using gradient vector flow(GVF)	Volume overlap(DSC)=94.2% Accuracy = 3.7 mm
Nader H. Abdel-massieh *et al.*	2011	15	Automatic	1) Isodata thresholding technique 2)Mean shift filter 3)automatic thresholding using 64 windows 4)morphological filling	Force-driven optimized active contour (snake**)**	Liver volume Sensitivity=95% Specificity=99.2%
Casciaro *et al*	2011	25	Automatic	1)Mean shift filter 2)stastics adaptive threshold initialization(64 squared regions)	Graph-cut algorithms Active contour(GVF)	DSC=96.17%
Elaziz *et al.*	2014		Automatic	1)median filter 2)image simplification(resize) 3)Morphological functions(erosion)	Region growing	

3.2 Tumor segmentation

To face the challenge of tumor boundary extraction, tumor segmentation has been widely covered in the literature in recent decades and continues to be a growing field with open research problem. From last three decades, a lot of research has been carried out to design an accurate segmentation algorithm. Several segmentation approaches have been introduced in recent years to overcome difficulties of tumor boundary extraction.

[11] Elaziz *et al*. conducted the experiments on liver as well as tumor surfaces. They used region growing method along with erosion to segment liver and tumor surfaces. They used the combination of intensity analysis and region growing for tumor segmentation and erosion in preprocessing steps and achieved Sensitivity=96.2%, Specificity=99.2%. By the implementation of region growing, it is concluded that region growing method is best employed on homogenous CT images where boundaries of different regions are well defined and have very similar intensity distribution. In region growing methods different choices of seed points can give different segmentation results.

[12] A comparative study between ten automatic and semiautomatic method has been done by Hienman *et al.* for liver segmentation on contrast enhanced CT images. From the study it is concluded that semi-automatic methods give better segmentation accuracy and consistent in segmentation quality.

[13]Abdel *et al*. proposed a method for tumor segmentation in which contrast stretching is done to increase the contrast between tumor and liver, after that slices of CT images are added to itself. Further guassian blurring, isodata thresholding and morphological filtering of image is done to extract tumors from CT images. This method gave good results in case of large tumors. However, in case of small and heterogeneous tumors the difference between manual and automatic segmented tumors is considerable.

[14] A comparative study is done on eight different deformable models of snakes and level set by L. He *et al.*, They choose original snakes, topological snakes, GVF, balloon force based active contour in the study of snakes which overcome the drawbacks of original snakes by enhancing the property of edge based external forces to track the boundaries. Similarly they studied original level set and geodesic active contour in context of level set formulation and concluded that GVF gives best segmentation results on different types of real images. Many methods have been employed for preprocessing [15-21].

[22] L.K. Haaitsma reviewed and discussed merits and demerits of tumor segmentation methods. They categorize their study on the basis of easy to use automatic method, general applicability and best suited for small size tumors. They observed that the method employed by Li *et al.* gives segmentation results on different types of tumors and complexity [23].

Level set method is subcategorized into edge and region based approaches. The implementation of these approaches finds different shortcomings in case of liver tumor segmentation because of low contrast and intratumoral heterogeneity.

[23] Li *et al.* introduced a new stopping function which exhibits the properties of both region and edge based characteristics for tumor segmentation on contrast enhanced CT images [20]. The functionality of stopping function depends upon the value of enhanced object indicator function having a parameter which will act as normal edge indicator function for zero value and if it is 1, it will use the region information of image. They achieved segmentation results on contrast enhanced CT dataset validated on two dataset with AOE=12.75% and relative volume difference (RVD) =4.28%.

[24]Osher and Sethian introduced a simple framework which consists of a speed term that moved in normal direction with no stopping term which can stop this speed term at certain point. In context of image process analysis, level set method was first introduced by Casseles *et al*. [25] and Malladi *et al*. [26] for image segmentation.

[26] Malladi et al. introduced a level set function which was a combination of curvature based speed term and gradient based stopping term. In this new method the need of initialization at the boundary of object was completely eliminated. Algorithm was able to split and merge in multiobject image and can change its topology.

[27] Hsu *et al*. proposed a level set method on synthetic images in which speed function with multiple thresholds is introduced to detect the boundaries of multiple regions of interest in image where multiple threshold values were decided automatically by using Fuzzy C-means method and stopping function was an inverted gradient of the image .

[28] Smeets *et al*. introduced a level set framework on CT tumor images where evolution of level set occur according to a speed function which is obtained by fuzzy pixel classification and stopping term is obtained by inverting the gradient of image[19]. Their method shows accurate

results on contrast enhanced images where tumor edges have high intensity difference with average overlap error(AOE) of 32.6% and average volume difference of 17.9%.

[29] Yang *et al*. reported a hybrid segmentation method for liver segmentation where an optimized initial liver region is detected by using fast-marching level set method marked by user and a threshold-based level set method is used for extraction of actual liver region based on initial liver region. In initial region formation a gradient-based sigmoid function is used as a speed function where α and β two parameters are added to increase the intensity difference between liver and surrounding areas and final liver region is obtained by incorporating threshold based level set method. They compare their results with region growing method and also achieved a similarity index = 97.6 ± 0.5%; false positive error = 2.2 ± 0.7%; false negative error = 2.5 ± 0.8%; average symmetric surface distance (ASD) = 1.4 ± 0.5 mm.

[30]Zhang *et al*. proposed a region based signed pressure force term instead of edge stopping function. It improves the conventional level set method by avoiding the calculation of reinitialization and calculation of signed distance function. But this method is based on region based stopping criteria so it cannot be applied on heterogeneous images having distinct intensity values.

Table 2.3 Previous year research work on level set method:

Author	**Year**	**Image type**	**Level set**	**Approach**	**Evaluation parameter**
Osher and Sethian	1988	-	Fundamental level set formulation	-	-
Malladi and Sethian	1995	Synthetic images	Introduce for shape recovery.	Edge based	-
Smeets *et al.*	2009	10 CT real image dataset		Edge based	AOE=32.6% AVD=17.9%
Li *et al*.	2010	Synthetic and real images(CT and MRI)	Distance regularized level set method	Edge based	-
Hsu *et al.*	2010	Synthetic images with different range of intensity values.	Multithreshold level set method.	Edge based	-
Zhang *et al.*	2010	Synthetic and real images	Selective Binary and Gaussian Filtering Regularized Level Set	Region based	-
Li. *et al.*	2011	MR images.	Level set method for heterogeneous	Region based.	-

			images.		
Li *et al.*	2012	2 CT image dataset.	Integrated image gradient and region competition	Region and edge based	AOE= 12.75 ± 5.76%, RAD =4.28 ± 9.58%, ACD=1.66 ± 1.09 mm, MCD= 4.29 ± 2.75mm
Yang *et al*.	2014	15 CT dataset	Hybrid method	Region based and edge based	SI = 97.6 ± 0.5% FPE = 2.2 ± 0.7% FNE = 2.5 ± 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

Reinitialization was introduced to overcome the difficulties of stability and errors however Li *et al*. [31] find serious problems in the implementation of reinitialization that is when and how this is to be applied [32]. Therefore they eliminate the need of reinitialization for regularization and introduce a distance regularization term and external energy term to drive the curve motion toward desired edge or boundary. Previous research work related to segmentation of tumor using level set and its respective variants is shown in table 2.3.From the above mentioned methods, it is concluded that level set method was best employed on contrast enhanced images where intensity difference between tumor and surrounding liver is large enough. Level set methods exhibit the problem of over segmentation and under segmentation in case of heterogeneous tumors and tumors with very small intensity difference in comparison to liver surface. It also encounters leakage problems at weak edges and gives false segmentation results.

CHAPTER 4
DEFORMABLE MODELS

Most of the methods employed on liver and tumor CT images are failed to segregate them from surrounding area due to irregular shapes and weak edges of liver and tumor boundaries. However, these methods are best employed on high contrast homogenous liver and tumor images and give false boundary detection in the presence of heterogeneity. The difficulties of over segmentation and misclassifications are tried to solve using deformable models which incorporate both spatial and image information. Active contour deformation in deformable models takes place by minimization of contour energies i.e. internal energy (from contour) and external energy (from image). These models are based on either edge or region based approaches and sub-categorized into two categories based upon the mechanisms to deform the contour:

i) Snakes

ii) Level set methods.

4.1 Snakes:

Original Snakes also called parametric contours was first introduced by Kass *et al.* [34]. The internal energy in snakes is based on curvature of the image which maintains the smoothness of contour while the external energy drive the contour towards the desired feature of the image. In active contour models, curve $c(p,t)$ is parameterized by points p where $p \in [0,1]$, different values of p corresponds to different points on the curve. The general curve evolution with certain velocity in normal direction is expressed as

$$\frac{\partial c(p,t)}{\partial t} = VN \tag{4.1}$$

Where V is speed function that directs the motion of active contour towards desire feature of image and N is the inward normal vector to the curve $c(p,t)$. The basic active contour exhibits various limitations such as

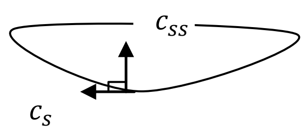
i) External energy dies out whenever it moves away from image boundaries that means capture range of snake is very small.

ii) Snake is parametric active contour therefore it cannot change its topology without the aid of external mechanism.

iii) The boundaries of contour are taken close to the boundary of object (ground truth) because noise of the image can pull the contour towards local energy minimum instead of ground truth. To overcome these drawbacks several researchers proposed different approaches to improve original snake. The mathematical fundamentals of deformable contours arrive from geometry, physics and approximation theories. Geometrically, A planar curve c(p) is defined by

$$c(p) = \{x(p), y(p)\} \tag{4.2}$$

Curve $c(p)$ is parameterized by p where $p \in [0,1]$ for every value of p we get a point $x(p)$ and $y(p)$ on the curve.



In a curve, boundaries are closed therefore curve can be defined by

$$c(0) = c(1)$$

The unit tangent $\underset{t}{\rightarrow}$ of the curve is given by the derivative of the function which is expressed as

$$\underset{t}{\rightarrow} = \frac{c_p}{|c_p|} = c_s \tag{4.3}$$

Where c_s is the unit arc length We know the inner product of unit vectors is equal to unity which is given by

$$< c_s, c_{ss} >= 1$$

Let's take the derivative of inner product

$$\frac{\partial < c_s, c_{ss} >}{\partial x} = \frac{\partial(1)}{\partial x} \tag{4.4}$$

$$2 < c_s, c_{ss} >= 0 \tag{4.5}$$

$$\Rightarrow \; c_s = k \underset{n}{\rightarrow} \tag{4.6}$$

c_{ss} is the double derivative where k is the curvature which tells about how much tangent is changing with respect to time. The curve is evolved with a velocity v is given by

$$c_t = \underset{v}{\rightarrow}$$

This velocity vector is divided into tangential and normal component. In the given equation the tangential do not change the shape of evolving curve. Therefore curve is only defined by its normal component.The curvature motion in normal direction is defined by

$$c_t = k \underset{n}{\rightarrow} \tag{4.7}$$

Cases:

$c_t = \underset{n}{\rightarrow}$ when k=1, curve will have constant flow.

$c_t = K \underset{n}{\rightarrow}$ When k have certain value, curve will have curvature flow which regularize into a circle.

$c_t = k^{1/3} \underset{n}{\rightarrow}$, curve will have equi-affine flow and curve will regularize into an ellipse.

4.1.1 Geodesic Active contour:

In image processing, Geodesic active contours are the contours in which the velocity function in normal direction is modified by introducing stopping function which is derived from image. In original curve evolution equation curvature of the curve which deforms with respect to time will collapse with time at a point or will vanish at a point. But in the context of edge detection in image processing, we want that curvature to collapse at certain condition that is at the edge of the image. Therefore velocity function is designed in such a way to fulfill this condition. We know that gradient of an image has high values at the edges of image. By taking the advantage of this property, a function g is defined which will have low values at the boundary/edge of the image. Therefore g is defined as

$$g = \frac{1}{\Delta I}$$

Where ΔI is the gradient of image, when this g function will have small values which is approaching to zero, curve will stop. The resulting formulation is given as

$$c_t = (g(x,y)k - < \nabla g(x,y), \underset{n}{\rightarrow} >) \underset{n}{\rightarrow} \tag{4.8}$$

In case of very weak edges, extra term $\nabla g(x,y)$ is used to make the stopping term stronger.

4.1.2 Calculus of variations:

In regular calculus, the minimum of a point or a function is obtained by moving the point in the direction of negative of derivative of function$f$.

$$\frac{\partial x}{\partial t} = -\frac{\partial f}{\partial x} \tag{4.9}$$

In calculus of variations, functions are made to get the minima or maxima of functional (set of definite integrals which consists of functions and their derivatives). Therefore, these stationary functions are the states where the rate of change of functional is zero. The necessary condition to attain a minima or maxima is Euler langrage equation.

$$\frac{\partial u}{\partial t} = -\frac{\partial E(u)}{\partial u} \tag{4.10}$$

Where $E(u)$ is the Euler langarange equation. Therefore on the curve function will move in the direction of langrage equation.

4.1.3 Potential functions(g):

Gradient of an image is high where there is a transition from one intensity value to another, in other words gradient gives us the edges of an image. That $g(x, y)$ is the reciprocal of gradient of image. Therefore $g(x, y)$will attain minimum values at the boundaries or edges that function is often called as potential function. In the graph the potential function will have minimum values at edges and can be seen as a well in the graph of g function. In case of weak boundaries $\nabla g(x, y)$ will trap the function to its minimum values.

4.1.4 Active contour and its evolution:

In basic contour evolution, the first step is to find the g function which is obtained using

$$g = \frac{1}{1 + |\nabla G_\sigma * I|^2} \tag{4.11}$$

Where G_σ is a Gaussian function with standard deviation σ which is convolved with image to smooth the image. Edge indicator function exhibit low values at the boundary of object. This function is integrated and in this way curve evolution takes place. Active contour model is swiftly becoming popular for segmentation in image processing due to its tracking property to detect edges. A similar technique of energy minimization in segmentation is getting popular nowadays. level set technique is similar to active contour in many aspects like same energy minimization property is used to segment a particular image. level set method is mainly divided into two classes –edge based model and region based model. level set method is generally rely on partial differential equations(PDE). Comparative study of both methods has been done because they are very similar in context of their principle and working. Here we are trying to figure out the difference between them and which one will give more accurate result.

4.2 Level set method:

Level sets are the sets on which the function is constant. This is an implicit representation where instead of parameterizing the curve, a function is assigned to the curve. Osher and Sethian introduced a different framework to define the curve evolution known as level set framework. Level set method is an implicit representation of curve where instead of parameterzing the curve $c(p,t)$, the curve is represented by a zero level set function of higher dimension $\varphi(x,y,t)$ which takes zero values on the curve, negative values inside the curve and positive values outside the curve.

$$c(p,t)=\{(x,y)|\varphi(x,y)=0\} \tag{4.12}$$

Where $\varphi(x,y)$ can be defined as a distance function whose value is negative inside the curve and outside the curve.

4.2.1 Properties of level sets:

a) Normal vector

Normal vector on a curve is defined by

$$N=-\frac{\nabla\varphi}{|\nabla\varphi|} \tag{4.13}$$

Proof: we know from the definition of level sets. Zero level set has zero values along the curve. Taking the derivative of above, by chain rule

$$\varphi_s(x,y)= \quad \varphi_x x_s + \quad \varphi_y y_s =<\nabla\varphi,\underset{T}{\rightarrow}> \tag{4.14}$$

$$\Rightarrow \qquad <\frac{\nabla\varphi}{|\nabla\varphi|},\underset{T}{\rightarrow}>=0 \tag{4.15}$$

$$\Rightarrow \qquad \frac{\nabla\varphi}{|\nabla\varphi|}\perp\underset{T}{\rightarrow} \tag{4.16}$$

$$\Rightarrow \qquad N=-\frac{\nabla\varphi}{|\nabla\varphi|} \tag{4.17}$$

b) Level set curvature:

Curvature is given by

$$k = div(\frac{\nabla\varphi}{|\nabla\varphi|}) \tag{4.18}$$

Where div is the divergence of 1st derivative.

Proof: As discussed earlier, level set has zero change along the curve, that implies double derivative will also be zero that is

$$\varphi_{ss}(x,y) = \frac{d\,(\ \varphi_x x_s + \ \varphi_y y_s)}{ds} = \frac{d<\nabla\varphi, \underset{T}{\rightarrow}>}{ds} = 0 \tag{4.19}$$

$$\Rightarrow \quad <\frac{d<\nabla\varphi, \underset{T}{\rightarrow}>}{ds}> + <\nabla\varphi\ , k\ N> \ = 0 \tag{4.20}$$

$$\Rightarrow \quad k < \varphi, \frac{\nabla\varphi}{|\nabla\varphi|} >= -< [\varphi_{xx}x_s + \varphi_{xy}y_s, \varphi_{xy}x_s + \varphi_{xy}y_s], \frac{\nabla\varphi}{|\nabla\varphi|} > \tag{4.21}$$

Geodesic active contour in level set framework can be represented as

$$c_t = (gk - < \nabla g, \underset{N}{\rightarrow} >) \underset{N}{\rightarrow} \Leftrightarrow div\left(g\frac{\nabla\varphi}{|\nabla\varphi|}\right)|\nabla\varphi| \tag{4.22}$$

c) Level set formulation:

Curve in level set formulation as defined above is given by

$$C = \{(x,y)|\varphi(x,y) = 0\} \tag{4.23}$$

Differentiate above equation with respect to time

$$\frac{\partial\varphi(x,y,t)}{\partial t} = 0 = \varphi_x x_t + \varphi_y y_t + \varphi_t \tag{4.24}$$

$$\Rightarrow \quad -\varphi_t = \varphi_x x_t + \varphi_y y_{t=} < \nabla\varphi, c_t >=< \nabla\varphi, \underset{V}{\rightarrow}\underset{N}{\rightarrow}> \tag{4.25}$$

$$\Rightarrow \quad = \underset{V}{\rightarrow} < \nabla\varphi, \underset{N}{\rightarrow} > \qquad \left[\underset{N}{\rightarrow} = -\frac{\nabla\varphi}{|\nabla\varphi|}\right]$$

$$\Rightarrow \quad \varphi_t = \underset{V}{\rightarrow} |\nabla\varphi| \tag{4.26}$$

Therefore in level set framework curve will move with velocity $\underset{V}{\rightarrow}$ in normal direction. This velocity vector gives direction and speed at each point. Therefore curve is the set of points where $\varphi(x,y) = 0$ at t=0 and at later point of time the zero level set is defined by $\varphi(x,y,t)$. In this framework, normal vector of the curve is represented by $N = -\frac{\nabla\varphi}{|\nabla\varphi|}$. Therefore the curve evolution in level set framework is formulated as

$$\frac{d\varphi}{dt} + \underset{V}{\rightarrow} |\nabla\varphi| = 0 \tag{4.27}$$

Where curve will evolve or deform according to a speed function V. The speed function in original level set consists of curvature term and stopping function term which are equivalent to internal and external energy terms in snakes respectively. Conventional level set methods face the problem of irregularities during the evolution of level set function (LSF) which leads to distortion of stability and numerical errors. To maintain the stability during the the evolution of level set function it is necessary that it must be smooth near the zero level set. This condition is fulfilled by defining LSF as signed distance function which makes equal angle with both *x* and *y* direction and propagate in normal direction which is expressed as $|\nabla\varphi| = 1$. To attain this property, curve is stopped and reshaping of degraded LSF is done after fixed interval of time termed as reinitialization. Different methods have been employed by different researchers for reinitialization. A standard method for reinitialization is

$$\frac{\partial\Psi}{\partial x} = sign(\varphi)(1 - |\nabla\varphi|) \tag{4.28}$$

Where sign is sign function. A standard method for reinitialization is fast marching method where distance is computed to the next nearest point on interface and in this way curve is marched outward [32].

The level set method is a versatile tool that is used to trace the interfaces that will separate image into different regions. Most attractive feature of a level set is that their topology can change with time. Level set method is an implicit representation of active contours. In level set method, instead of parametrizing the curve on a plane, a function is assigned to perform numerical computations. The versatility of level set method can be justified by the fact that level set method can characterize contours of complex topologies and can handle different changes in topologies like splitting and merging in efficient way. This property of splitting and merging is not successfully met in conventional parametric contour models. These special features of level set method have promoted it for further research and applications in different scientific and engineering fields.

4.2.2 Comparison of snakes and level set method:

Active contour method and level set methods has been widely used in segmentation of liver and tumor due to their inherent capability to segment the liver portion from abdomen CT images. Comparative study of both methods has been done because they are very similar in context of their principle and working. Here we are trying to figure out the difference between them and which one will give more accurate result. 3-D liver reconstruction goes through following steps (i) Preprocessing (ii) Segmentation of liver (iii) 3-D Volume reconstruction. Proposed procedure is shown in fig .1

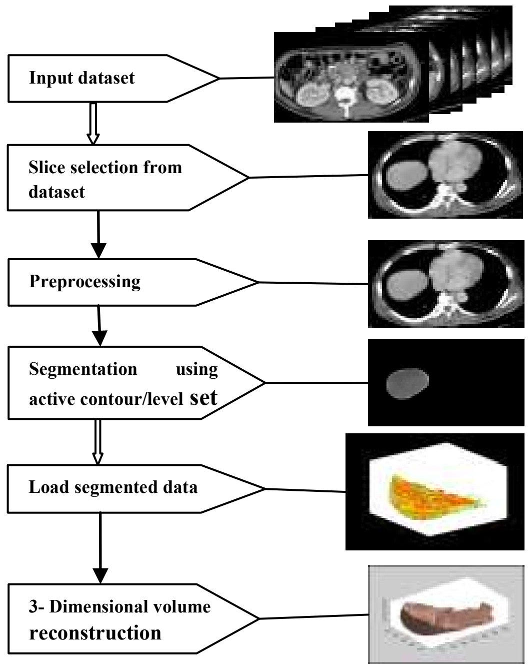


Fig.4.1 Flowchart of Liver segmentation using active contour and level set methods in order to get 3-Dimensional volume.

Preprocessing of CT images is primarily done to assemble all abdominal CT images which has different size and liver portion and to remove noise caused due to CT scan machine. CT information of an individual patient is confidential therefore CT dataset is resample to 370x417 dimensions to remove patient information and to decrease overall processing time of computer aided diagnose(CAD). In Level set method implementation, morphological operations is performed as level set works on split and merge framework. So it will put down small dark spots on CT image. Which can lead to false liver portion detection and overall performance evaluation will mislead the results. Both methods are tested on contrast enhanced images.

4.3 Distance regularized level set method:

Li et al. states that reinitialization face different problems like when and how this is to be applied and they also found serious problems in the implementation of signed distance function as reinitialization method. They state that in conventional level set implementation there is no term to preserve level set function as signed distance function. To overcome these drawbacks they eliminate the reinitializtion process and introduce a distance regularization term and external energy term to drive the curve motion toward desired edge or boundary.

4.3.1 Energy formulation with distance regularization by li et al.:

Reinitialization was introduced to overcome the difficulties of stability and errors however Li *et al*. find serious problems in the implementation of reinitialization that is when and how this is to be applied [31]. Therefore they eliminate the need of reinitialization for regularization and introduce a distance regularization term and external energy term to drive the curve motion toward desired edge or boundary. An energy term is introduced which derives the contour to desired position. Thus energy functional $E(\varphi)$ is represented by

$$E(\varphi) = \mu D_r(\varphi) + E_{external}(\varphi) \tag{4.29}$$

where $D_r(\varphi)$ is distance regularization term, μ is constant defined for μ>0 and $E_{external}$is external energy defined by feature of image like edge, line or region. External energy is defined using edge indicator function g on an image in a domain s by

$$g = \frac{1}{1 + |\nabla G_\sigma * \mathrm{I}|^2} \tag{4.30}$$

Where G_σ is a Gaussian function with standard deviation σ which is convolved with image I to smooth the image. Edge indicator function g exhibit low values at the object boundary. Energy functional $E(\varphi)$ for a level set function: $s \rightarrow \mathcal{R}$ is termed as

$$E(\varphi) = \mu D_r(\varphi) + \lambda length_g(\varphi) + \alpha Area_g(\varphi) \tag{4.31}$$

Where energy functional $length_g(\varphi)$ and $Area_g(\varphi)$ have coefficients $\lambda > 0$, $\alpha \in \mathcal{R}$ and are defined as

$$length_g(\varphi) = \int_s g\delta(\varphi)\,|\nabla\varphi| dx \tag{4.32}$$

$$Area_g(\varphi) = \int_s gH(-\varphi)dx \tag{4.33}$$

Where δ and H are the Dirac delta functions and Heaviside function respectively.

The energy functional $length_g(\varphi)$ is used to compute the line integral of function g along the zero level set. This energy gets minimized at the boundary of zero level contours. On the other hand, $Area_g(\varphi)$ is used to compute the weighted area of region s. This area functional is used to speed up the motion of active contour. As described earlier the level set function takes negative values within the zero level contours and outside the contour it takes positive values. Therefore the coefficient α of $Area_g(\varphi)$ should be positive in case of initial contour is placed outside the tumor to shrink the zero level contour in the level set evolution and negative to expand the contour in case of initial contour is placed inside the tumor. In energy functional $Area_g(\varphi)$, g is used to slow down the expansion and contraction of active contour when it reaches at the boundary of active contour. Therefore g is a stopping function to stop the contour at the boundary of image. Thus the energy functional is given by

$$E(\varphi) = \mu \int_S P(|\nabla\varphi|)\, dx + \lambda \int_S g\delta(\varphi)\, |\nabla\varphi| dx + \alpha \int_S gH(-\varphi) dx \tag{4.34}$$

Where first term is distance regularization term and second, third is external energy term. The spatial derivatives in the time dependent level set function $\varphi(x, y, t)$ were approximated using central difference whereas, the temporal derivative was approximated using forward difference, level set evolution equation is descretized by finite forward difference scheme with spatial index(*i,j*) and temporal index *t*.

CHAPTER 5

MODIFIED DISTANCE REGULARIZED LEVEL SET METHOD

5.1 Motivation:

Conventional level set method proposed by Osher and Sethian[25] and in context of image processing proposed by Malladi *et al.* [26]was able to handle topological changes in the image and was extensively applied to model complex shapes. A number of modifications were done in recent years for better convergence and to handle the problem of reinitialization in conventional level set methods. One approach was introduced by Li *et al.* [31]to eliminate the need of reinitialization by introducing double well potential term for regularization and they used edge based energy functional to converge or stop the contour at the boundary of interfaces having distinct intensity characteristics. The spatial derivatives were approximated using central difference scheme in x and y direction i.e. $\frac{\partial I}{\partial x}$ and$\frac{\partial I}{\partial y}$. DRLSE method was performed on CT tumor images collected from different clinical centers. It shows leakage problem at the boundary of tumor as shown in fig.2 where red line shows the contour evolution and yellow arrows show the leakage of DRLSE method at the boundary of tumor. First a comparative study is performed in this work where, the central difference scheme was replaced with upwind scheme to approximate spatial derivative which is used to calculate the stopping function. Initial experiment was made to compare the effect of central difference scheme and upwind scheme. This initial comparative study shows upwind scheme converges at the boundary of tumor contour with higher accuracy than that of central difference scheme. The results of this experiment can be visualized clearly on the sample image as shown in fig.5.1. These initial results motivate us to design a upwind scheme with higher number of pixels into consideration to improve the boundary (exact) definition of tumor. The inspiration is the work of Mittal *et al*. [33] where the higher order pixels are used to improve the definition of texture in ultrasound images.

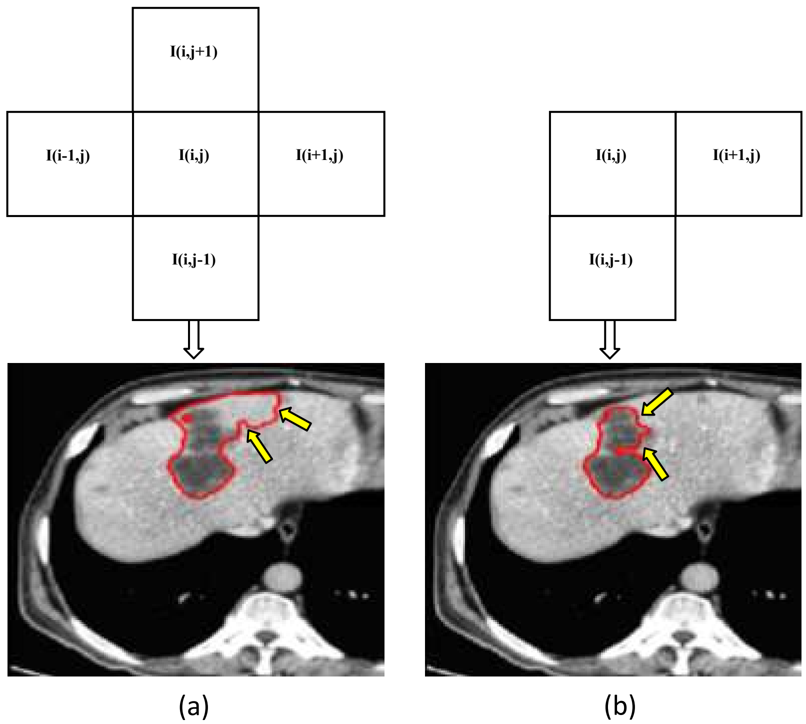


Fig.5.1 A comparative analysis of central and upwind scheme on CT tumor image:(a) template used in central difference scheme and its implementation on CT tumor image and (b) template used in upwind scheme and its implementation on CT tumor image. Red lines-Contour evolution using level set method; Yellow arrow-leakage at the boundary of tumor.

5.2 Method development:

A modified distance regularized level set evolution method which incorporates a distance regularized level set method and work inspiration from Mittal *et al*. is designed to efficiently segment hepatic tumor. Segmentation process is summarized in fig.5.2 which illustrates i) preprocessing of contrast enhanced CT images using CLAHE ii) evolution of MDRLSE method iii)final segmented tumor result and iv) 3D volume reconstruction by stacking 2D CT image slices. Fig.5.3. shows the step by step response of proposed MDRLSE method on CT tumor images. Fig. 5 (A) shows the input CT abdomen image which is further simplified or cropped for better visualization and to reduce processing time. Fig 5(B) is the contrast enhanced image obtained by the application of CLAHE on CT image with initial marked ROI in rectangular form in red lines. Fig. 5(C) shows the evolution of initial contour after 50 iterations. Fig. 5(D) shows the segmented tumor on CT image and fig. 5(E) is the final segmented tumor.

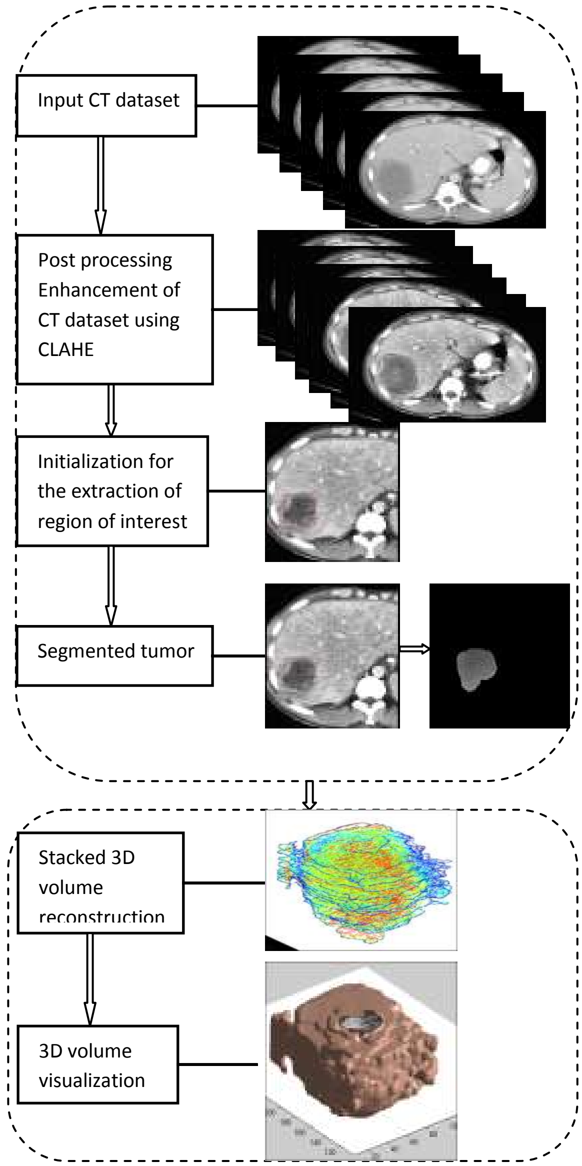


Fig.5.2 Block diagram representation of Modified distance regularized level set method

5.2.1 Preprocessing:

Abdominal CT images consist of different artifacts during the acquisition of image from CT scan machine. Preprocessing of CT images is necessary to eradicate the noise to further improve the contrast of tumor with respect to background. Contrast of CT abdominal tumor image is enhanced for well differentiation of hepatic tumor from surrounding liver tissues with comparable intensities. In the present work contrast-limited adaptive histogram equalization (CLAHE) is used for contrast enhancement of tumor images. The CLAHE algorithm divides the image into non-overlapping regions and histogram equalization is applied to each region. This smoothes the grey values and hence makes hidden features of the image more visible. For a 512x512 dimensional image, it is divided into 64 equal sub regions.

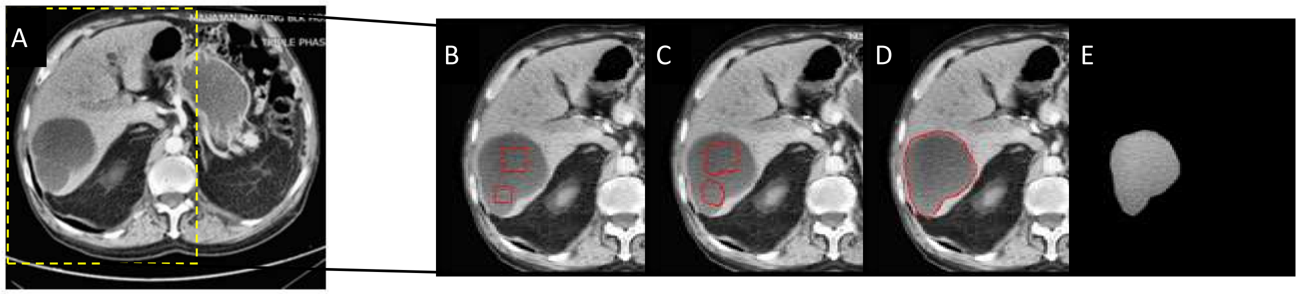


Fig.5.3 Step by step response of level set method on homogenous hepatic tumor. (A)Original CT tumor image.(B) Initialization of initial contour(ROI) inside the tumor surface.(C) Evolution of initial level set function after 50 iterations towards the boundary of tumor. (D) Final tumor boundary extraction in CT abdomen image. E) Final segmented tumor. Initialization(ROI) and contour is highlighted with red lines.

5.2.2 Proposed method

Distance regularized level set evolution method performs very well in case of distinct boundaries in the image, but in hepatic tumor segmentation, it fails to distinguish between liver and tumor boundaries due to very low contrast difference between liver and tumor boundaries. The value of edge indicator function which is a stopping function in external energy term takes very low values at the edges which stop the curve evolution at the boundary of image. In case of DRLSE method this g function is not so strong to converge at the weak edges and therefore leaks out at weak and saddle points. The spatial derivative in DRLSE method has been approximated using central difference scheme as described earlier which is represented by a template shown in fig.5.4. This term can be more accurately calculated by using a large-sized templates having higher number of neighborhood pixels. Modified methodology will give a better segmentation result in case of hepatic tumor segmentation with better convergence at weak edges. The experiment is devised by considering the two modifications in upwind scheme. Experiments are devised with three new templates of 3,4and 6 neighborhood pixels as shown in fig5.4.

5.2.2.1 Modified distance regularized level set method

The proposed MDRLSE method is explained in this section. In the DRLSE method as explained earlier the edge indicator function can be rewritten as

$$g(|\nabla_{Di}\mathrm{I}|) = \frac{1}{1 + |\nabla G_{\sigma} * \mathrm{I}|^2} \tag{5.1}$$

Where image I(x,y) is convolved with Gaussian filter to smooth the image and ∇_{Di} is gradient operator in different direction where direction is represented by Di={North,south,east,west}. For further simplification $|\nabla G_{\sigma} * \mathrm{I}|^2$is taken as f_{Di}. The descretization of space coordinates is done as

$x = ih, \quad where\ i = 0,1,2,3, \dots\dots\dots\dots, \mathrm{M}-1$

$y = jh, \quad where\ j = 0,1,2,3 \dots\dots\dots\dots, \mathrm{N}-1$

$\mathrm{I}_{i,j} = \mathrm{I}(ih, jh)$

Where the spatial step size is denoted by h and represents the distance between two consecutive pixels in x and y directions on the image of the size Mh X Nh. In numerical analysis, h is taken as 1, therefore the intensity of image pixel is represented as $\mathrm{I}_{i,j}$ at position (i, j). The spatial derivative $\frac{\partial \mathrm{I}}{\partial x}$ and $\frac{\partial \mathrm{I}}{\partial y}$ of image I(x,y) is approximated using central difference scheme. The central difference scheme in the x direction of image I(x,y) is calculated as

$$\nabla_{EW}\mathrm{I}(x,y) = \left(\frac{\partial \mathrm{I}}{\partial x}\right)_{i,j} = \frac{\mathrm{I}_{i+1,j} - I_{i-1,j}}{2\nabla h}$$

Where Δ_{EW} is the derivative in east-west direction. Similarly in y-direction, central difference is given as

$$\nabla_{NS}I(x,y) = \left(\frac{\partial I}{\partial y}\right)_{i,j} = \frac{I_{i,j+1} - I_{i,j-1}}{2\nabla h}$$

Therefore f_{Di} is given by

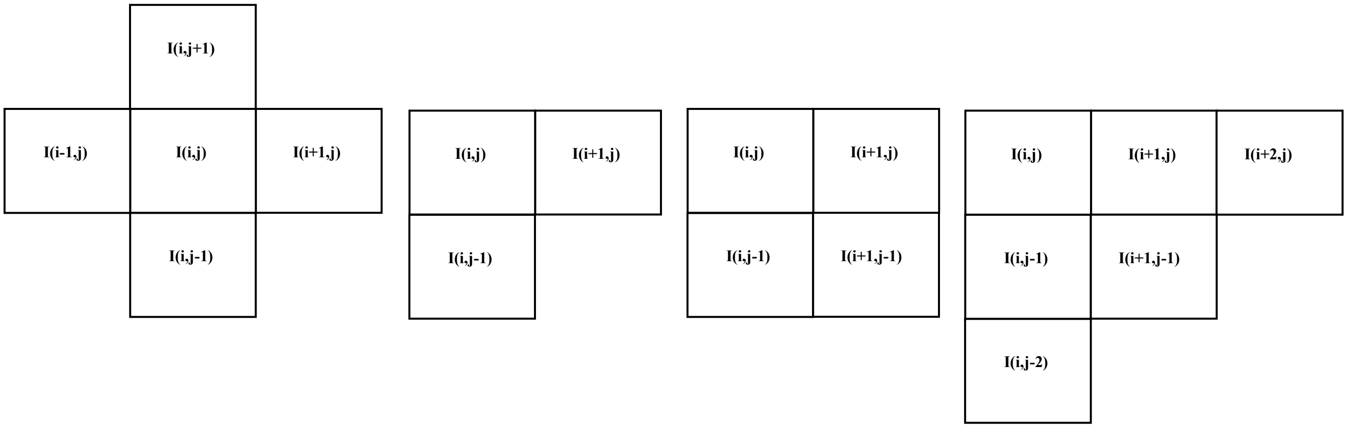
$$f_{Di} = \frac{\left(\nabla_{EW}I(x,y)\right)^2}{4} + \frac{\left(\nabla_{NS}(x,y)\right)^2}{4} \tag{5.2}$$

The neighborhood pixel representation of pixel (*i,j*) in template 5 is shown in fig.5.4(A) . In proposed method the calculation of upwind scheme derivative is done using three pixels in forward direction as shown in fig. 5.4(B) and termed as template 3. Further, the other two templates are named as template 7 and template 9 as shown in fig.5.4(C-D), respectively. Three set of experiments are performed using templates 3,4 and 6 to test the feasibility of proposed method.

Experiment I: In experiment I, template 3 is used for contour evolution which is the standard configuration of upwind scheme and is replaced by central difference scheme. The pixels at a distance h from the center pixels are

$I_{i+1,j}, I_{i,j-1}$

For these Pixels, spatial derivative approximations can be calculated as



(a) (b) (c) (d)

Fig.5.4 Templates of pixels used in(a) DRLSE method,(b)template 3 upwind scheme,(c) template 4 and (d) template 6 in MDRLSE method

$$\nabla_E \mathrm{I}(x,y) = \left(\frac{\partial \mathrm{I}}{\partial x}\right)_{i,j} = \frac{\mathrm{I}_{i+1,j} - \mathrm{I}_{i,j}}{h}$$

$$\nabla_s I(x,y) = \left(\frac{\partial I}{\partial y}\right)_{i,j} = \frac{I_{i,j} - I_{i,j-1}}{h}$$

$$f_{Di} = \left(\nabla_E I(x,y)\right)^2 + (\nabla_S I(x,y))^2 \tag{5.3}$$

Experiment II: In experiment II, template 4 is used for contour evolution. The pixels at a distance h from the center pixels are

$I_{i+1,j}, I_{i,j+1}$

Pixel at a distance $\sqrt{2}\,h$ from the central pixel is

$I_{i+1,j+1}$

These pixels in spatial derivative approximations can be calculated as

$$\nabla_{SE} \mathrm{I}(x,y) = \left(\frac{\partial I}{\partial x}\right)_{i,j} = \frac{I_{i+1,j-1} - I_{i,j}}{\sqrt{2h}}$$

$$f_{Di} = \nabla_E I(x,y)^2 + \nabla_S I(x,y)^2 + \frac{\left(\nabla_{SE} I(x,y)\right)^2}{2} \tag{5.4}$$

Experiment III: In experiment III, template 6 is used for contour evolution. The pixels at a distance h from the center pixels are

$I_{i+1,j}, I_{i,j+1}$

Pixel at a distance $\sqrt{2}\,h$ from the central pixel is

$I_{i+1,j+1}$

Pixels at a distance of $2h$ from the central pixel is given as

$I_{i+2,j,}, I_{i,j+2}$

These pixels in spatial derivative approximations can be calculated as

$$\nabla_E I(x,y) = \left(\frac{\partial I}{\partial x}\right)_{i,j} = \frac{I_{i+1,j} - I_{i,j}}{h}$$

$$\nabla_S I(x,y) = \left(\frac{\partial I}{\partial x}\right)_{i,j} = \frac{I_{i+1,j} - I_{i,j}}{h}$$

$$\nabla_{SE} \mathrm{I}(x,y) = \left(\frac{\partial I}{\partial x}\right)_{i,j} = \frac{I_{i+1,j-1} - I_{i,j}}{\sqrt{2h}}$$

$$\nabla_{SS} I(x,y) = \left(\frac{\partial I}{\partial y}\right)_{i,j} = \frac{I_{i,j} - I_{i,j-2}}{2h}$$

$$\nabla_{EE} I(x,y) = \left(\frac{\partial I}{\partial y}\right)_{i,j} = \frac{I_{i,j} - I_{i+2,j}}{2h}$$

$$f_{Di} = \nabla_E I(x,y)^2 + \nabla_S I(x,y)^2 + \frac{\left(\nabla_{SE} I(x,y)\right)^2}{2} + \frac{\left(\nabla_{SS} I(x,y)\right)^2}{4} + \frac{\left(\nabla_{EE} I(x,y)\right)^2}{4} \qquad (5.5)$$

5.2.2.2 Creation of new stopping function

In the last step of proposed method, a new stopping function is created from edge indicator function to stop at the boundary of image. New stopping function g_{mdrlse} is modified by modifying the spatial approximation; new stopping function is given by

$$g_{mdrlse} = \frac{1}{1 + f_{Di}} \qquad (5.6)$$

Where $g_{mdrlse}$the new stopping is function and f_{Di} is calculated from equations explained above. Therefore the proposed MDRLSE method is given by

$$E(\varphi) = \mu \int_{\Omega} P(|\nabla\varphi|)\, dx + \lambda \int_{\Omega} g_{mdrlse} \delta(\varphi)\, |\nabla\varphi| dx + \alpha \int_{\Omega} g_{mdrlse} H(-\varphi) dx \qquad (5.7)$$

Where first term is distance regularized term, second and third term is external energy term to stop the contour at desired boundary.

CHAPTER 6
EXPERIMENTAL SETUP

6.1 Experimental setup for liver segmentation method:

Comparative evaluation of liver segmentation using active contour and level set methods are performed on a dataset containing contrast enhanced 52 abdomen CT images. CT images of dimensions 514x514 are acquired from MAX hospital, Delhi, India. Both methods are performed on MATLAB version 8.

6.2 Experimental setup for tumor segmentation method:

6.2.1 Information and characteristics of patient dataset:

The robustness and applicability of experiments I, II and III were tested on three distinct datasets of hepatic tumor viz. HCC and metastasis. These datasets of individual patients were categorized into three different test cases depends on the intensity characteristics of tumors as shown in table 6.1. Test case #1 consists of 120(out of 150 CT image dataset) abdomen CT image slices of heptocellular carcinoma (HCC) tumors which are homogenous types of tumors. Test case #2 consists of 35 metastatic tumors of heterogeneous types with mixed tissue intensity. Test case #3 consists of 11 metastatic multiple tumors with small heterogeneity. Metastatic types of tumors were the most difficult types of tumor to be segmented because most of the segmentation methods such as thresholding and region growing were built on the similar intensity property of image. Imaging parameters were set at image size of dimensions 512x512 and slice thickness 5.0mm.

Table 6.1: Intensity characteristics and types of hepatic tumor dataset used in experiments:

Test case	Tumor type	Intensity characteristic of tumors	Number of CT slices with tumor cases in dataset(total number of CT slices)
Test case 1	Heptacellular carcinoma(HCC)	Homogenous/hypo intense tumor	35
Test case 2	Metastasis	Heterogeneous tumor with mixed tissue intensity	120(150 total cases)
Test case 3	Metastasis	Multiple tumors with some heterogeneity	11

6.2.2 Software and hardware implementation

The proposed method was implemented on Matlab®R2014a (8.3.0.532) by making the use of its image processing toolbox running on Windows7 home basic Windows edition. The software was executed on a Intel-VAIO computer with Intel(R) Core(TM) i3-2370M CPU @2.4 GHz processor with 4GB RAM memory.

6.2.3 Evaluation metrics

Quantitative analysis of hepatic tumor segmentation results is done by adapting evaluation frameworks. These frameworks are adapted in order to evaluate and validate the segmentation accuracy of proposed method. Reference segmentation called 'ground truth' and segmentation result is called 'level set segmentation' for each test case is evaluated by following metrics.

i)Dice similarity coefficient (DSC): Dice similarity coefficient is a index to measure spatial overlapping of ground truth result and segmentation result.

$$\mathrm{DSC} = \frac{2(\mathrm{S_g} \cap \mathrm{S_{seg}})}{\mathrm{S_g} + \mathrm{S_{seg}}} \tag{42}$$

Where S_g represent the ground truth segmentation and $\mathrm{S_{seg}}$ represent the level set segmentation of hepatic tumor. The 0 value of DSC indicates no spatial overlap 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.

ii) Relative volume difference (RVD)

Relative volume difference is calculated from the absolute change between the ground truth segmentation and level set segmentation of hepatic tumor values, and it is the ratio of the difference between level set segmentation of hepatic tumor to that of ground truth segmentation. In the context of tumor segmentation it is expressed as

$$\mathrm{RVD} = \frac{\mathrm{V_{seg}} - \mathrm{V_g}}{\mathrm{V_g}} \tag{43}$$

Where $\mathrm{V_{seg}}$ is level set segmentation volume result and $\mathrm{V_g}$ is ground truth segmentation volume result of hepatic tumor. Its 0 value indicates perfect segmentation and imperfect segmentation otherwise. 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 7
RESULTS AND DISCUSSION

7.1 Liver segmentation results using snakes and level set method:

Semiautomatic segmentation of liver is successfully executed and their 3D volume is reconstructed on all CT image slices. Steps involved in processing of active contour and level set method is shown in fig.7.1 and fig.7.2. In case of active contour, initialization is carried out manually by assigning initial contour points at the boundary of liver portion.

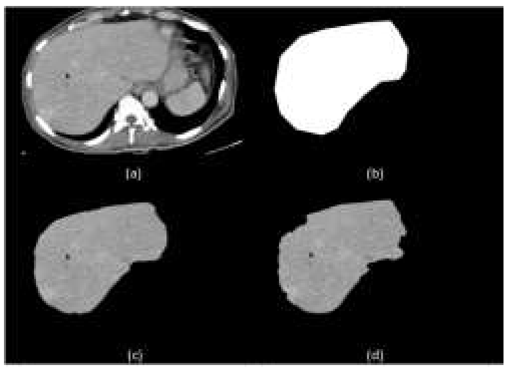


Fig.7.1 Different steps of active contour method(a)Original resized 377x417 CT image slice(b)Initial mask obtaibed after initialization(c)Liver portion obtained after 50 iterations (d)Liver portion obtained after 200 iterations.

Therefore, initialization is required in case of active contour method. Whereas in case of level set method, there is no need of initialization as if computer aided diagnose(CAD) is designed such a way that initial contour in any shape like rectangular or circular is initialized inside the liver portion. In level set method, level set function propagates at a constant speed function and contour stops at the boundary of the liver by a stopping function that is edge function. Due to absence of manual intervention processing time of level set is lesser as compared to active contour as is shown in table 7.1.Comparative study of segmentation results is performed by comparing both algorithm's results with clinically acquired CT images marked by radiologist. Comparative analysis of segmentation results can be seen visually in fig.7.3.Visual inspection gives almost same results on all 3 cases i.e. manual segmentation, active contour and level set Method. It can be seen in fig. 7.3 where area of cross section of liver in abdomen CT image is small and regular. Both methods give good segmentation result. But the cases like shown in fig.7.3 there is an irregularity in area of cross section of liver in abdomen CT image, active contour method has given a good segmented contour whereas in case of level set method there is

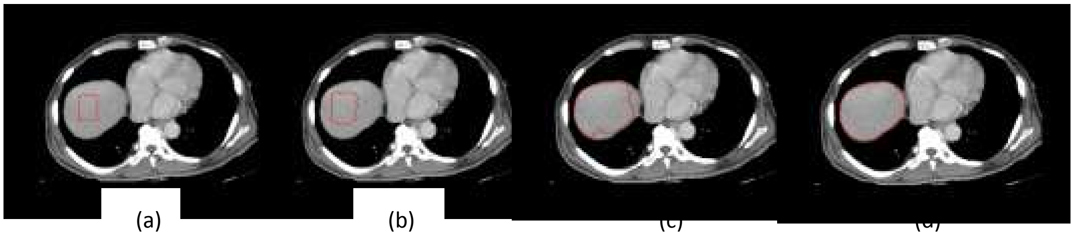


Fig.7.2 Different stages in level set method

leakage at the boundary of liver.

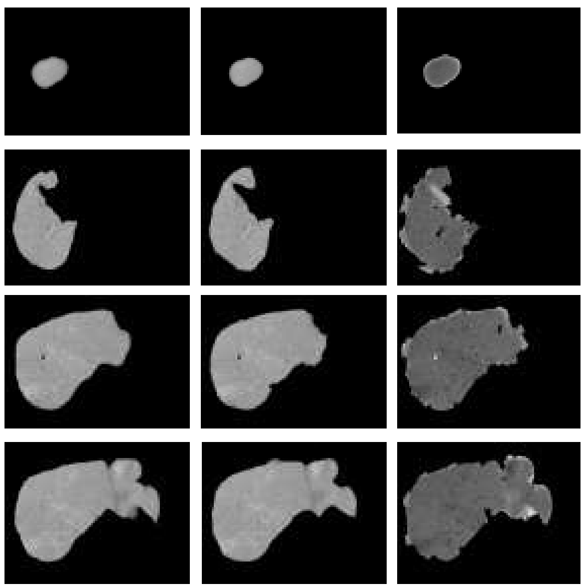


Fig.7.3 Results obtained from manual segmentation, active contour method and level set method (from left to right)from Different slices of abdomen CT image dataset(top to bottom)

Therefore it does not give an accurate segmentation result. Main drawback of level set method is leakage at the boundary. This is the main reason of false detection of edges in level set method. Active contour and level set method gives good segmentation result.

Table 7.1: Dice similarity coefficient result by using Active contour and level set method

CT slice no.	**Active Contour method**	**Level Set method**
CT slice1	0.9329	0.8874
CT slice2	0.9485	0.8983
CT slice 3	0.9569	0.9129
CT slice 4	0.961	0.9426
CT slice 5	0.9551	0.9486
CT slice 6	0.9555	0.9474
CT slice 7	0.9251	0.9529

CT slice 8	0.9585	0.9115
CT slice 9	0.9594	0.9461
CT slice 10	0.9703	0.954

Both methods give mean DSC of 93.52%±.62 and 89.48%±.76. Comparative analysis of both methods is shown in table 3. Therefore it can be clearly seen that Active contour gives better segmentation result.

Table 7.2: Comparison of liver segmentation results

	Active Contour method		**Level Set method**	
	Mean	**STDEV**	**Mean**	**STDEV**
DSC	93.52%	62.9%	89.48%	76.08%

Table 7.3: Processing time

	Active contour	**Level set**
Liver segmentation(seconds)	32.98	14.17

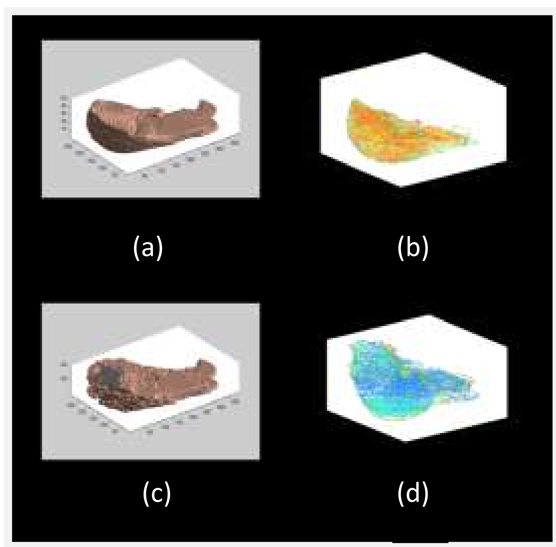


Fig.7.4:3D volume visualization (a-b)3D volume representation using active contour method which is smooth reconstruction of liver volume(c-d)3D volume representation using level set method with rough and irregular reconstruction of liver volume.

Active contour method gives improved 3D visualization result by 3D volume reconstruction of 2D CT image slices.

7.2 Tumor segmentation results using MDRLSE method

In this section, segmentation results of hepatic tumor will be discussed by employing all three experiments on all three test cases.

7.2.1 Parameter settings

The proposed MDRLSE method is configured with following parameters to get more accurate segmentation results i.e. λ, μ, α and Δt. For better segmentation results and to overcome the drawbacks of conventional level set method, the elimination of regularization term and introduction of double well potential to regularize the level set function used in the DRLSE method is used in similar fashion in MDRLSE method. The proposed method is not sensitive to μ and λ terms therefore they are fixed for all three experiments i.e. $\mu = 1.2(\pm 3)$, $\lambda=1.5(\pm 2)$. Weighted area term α, which gives extra driving force to the contour, is tuned according to the requirement of shrinkage and expansion of contour. Negative values of α is chosen to evolve the contour outward and positive values of α is chosen to shrink the initial contour. Further, small values of α is chosen to avoid leakage of contour at weak edges. In test case 1, parameter $\alpha=-2(\pm 5)$ was set to shrink the initial contour (ROI), whereas in test cases 2 and 3 area term was set at $\alpha=2(\pm 5)$. The value of time step is chosen in such a way to satisfy the courant condition $\mu\Delta t < 1/4$. In most of the cases $\Delta t > 1$, therefore in all three test cases $\Delta t = 2(\pm 20)$ was chosen to maintain stable evolution of contour. The values of Δt is chosen according to the texture of image. If the texture of image is smooth Δt will give comparatively good results even in large time steps but in case of irregular texture where each pixel will have different values smaller time steps were used such as in case of tumors. The convergence of contour at the boundary of tumor is achieved in the range of 400 ~ 600 iterations. For a fair comparison among all the experiments a common iteration values of 200, 400 and 600 are chosen in heterogeneous, multiple tumors and homogenous tumors cases respectively.

7.2.2Segmentation results:

In this section, tumor segmentation results by DRLSE and proposed MDRLSE methods on all three test cases are discussed qualitatively by the comparison of ground truth images marked by expert radiologist and segmented tumor extracted by proposed MDRLSE method. Quantitative findings of MDRLSE method were supported by two evaluation metrics i.e. DSC and RVD.Fig.7.5 shows the tumor segmentation results on all three test cases in which MDRLSE method found superior to DRLSE method. Initial marked ROI in red lines on contrast enhanced CT images is shown in A1, B1, and C1. Over segmentation in A2, B2, C2 (processed by DRLSE) is significantly removed in A3, B3, C3 (processed by MDRLSE Experiment I) respectively. Tumor segmentation gets better with MDRLSE experiment II(A4,B4 andC4) and gives correct boundary extraction results with the application of MDRLSE-experiment III as shown in A5,B5 and C5.These segmentation results can be observed in Fig.7.5 where ground truth segmentation marked by expert radiologist is indicated by yellow lines and segmentation results is shown by red lines. The results of qualitative evaluation in DRLSE method on three test cases are given below.

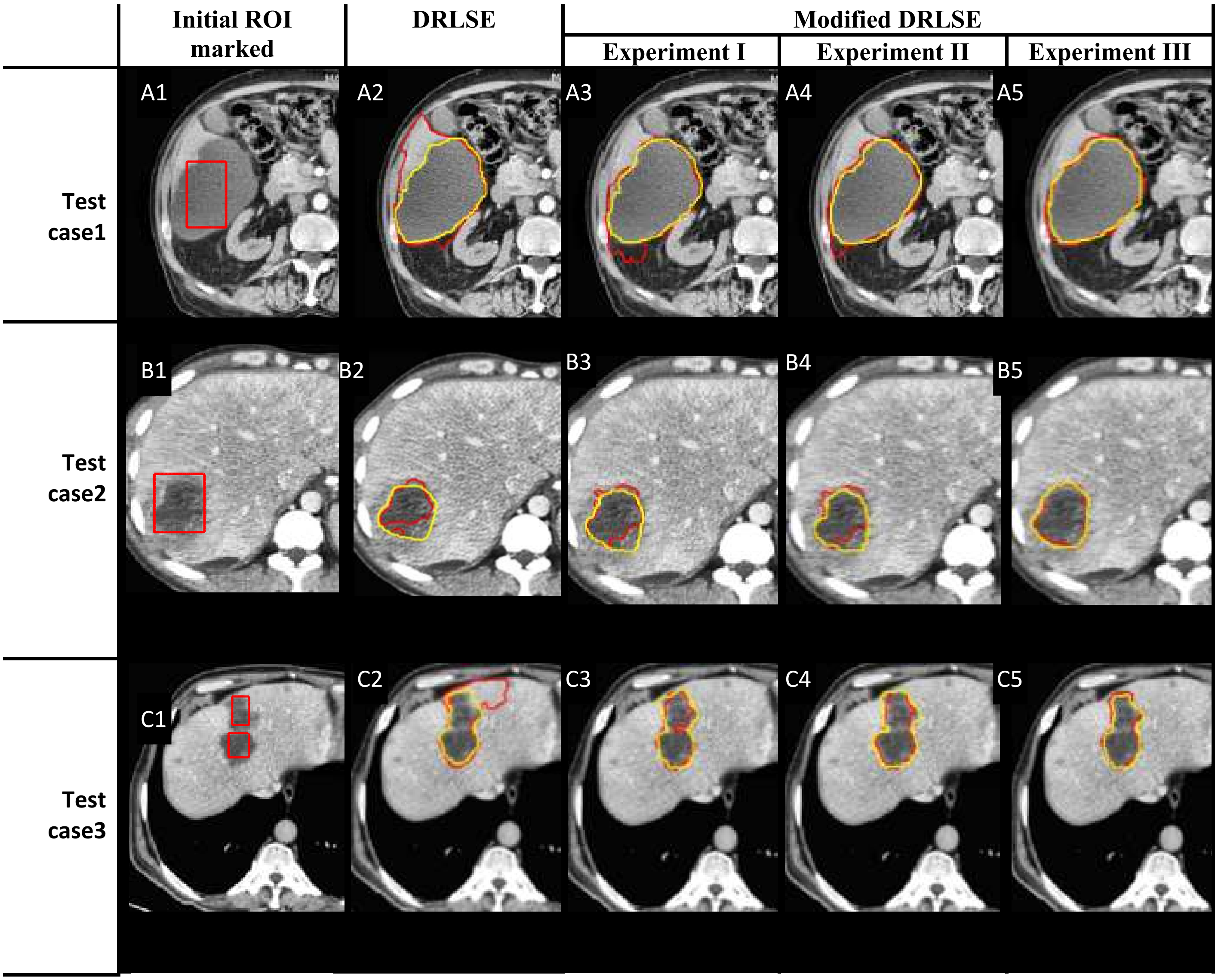


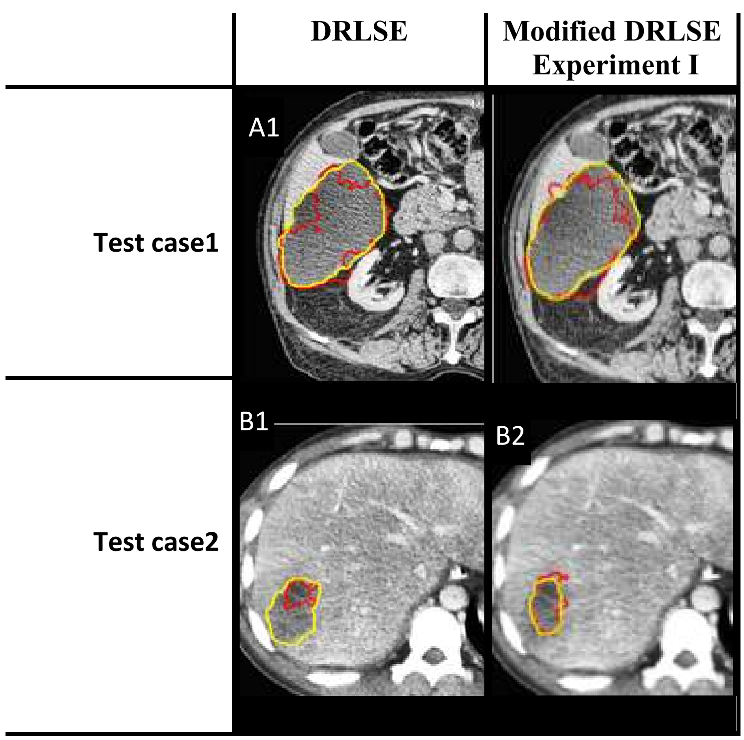
Fig.7.5 Comparative performance results of proposed method on test cases. Contour evolution using different methods is highlighted with red lines; over segmentation (leakage)

A: Test case 1
B: Test case 2
C: Test case 3

1: Initialization of contour (ROI)
2: Tumor boundary extraction using DRLSE method
3: Tumor boundary extraction using experiment I
4: Tumor boundary extraction using experiment II
5: Tumor boundary extraction using experiment III

i) Out of 130 tumor cases of HCC 5 tumors of good contrast gave good segmentation results comparable to ground truth segmentation result in test case #1. These are the cases of uniform intensity of tumor with distinct boundaries. From the visual inspection it can be clearly visualized that DRLSE method does not evolve with time and it encounter leakage problem at the boundary of tumor ii)Out of 18 tumor cases the segmentation results of only 3 tumors is comparable with ground truth tumor segmentation results in test case #2 iii) Test case #3 consists of a dataset of 11 CT images of metastasis tumors. DRLSE method gave very bad segmentation results and leaks out at the boundary of tumors and DRLSE failed to segment all 11 tumor cases of metastasis and leaked to adjacent liver region.

Experiment I: Experiment I use forward difference scheme with template 3 in which boundary leakage problem is reduced considerably and segment i) 15 tumors in test case #1 ii) 5 tumor cases in test case #2 cases and iii) No tumor in test case #3 compared to ground truth segmentation but overcome the leakage problem considerably. Fig.7.6 shows the comparison of experiment I and DRLSE with improvement in segmentation accuracy of tumor on all test cases.



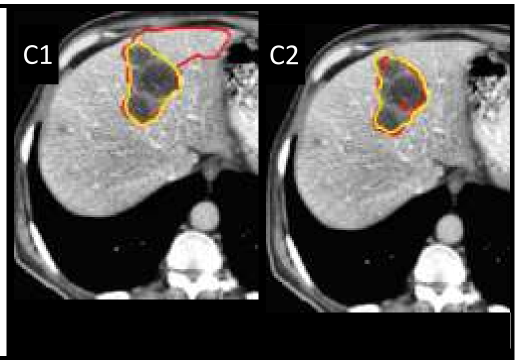
Test case3	

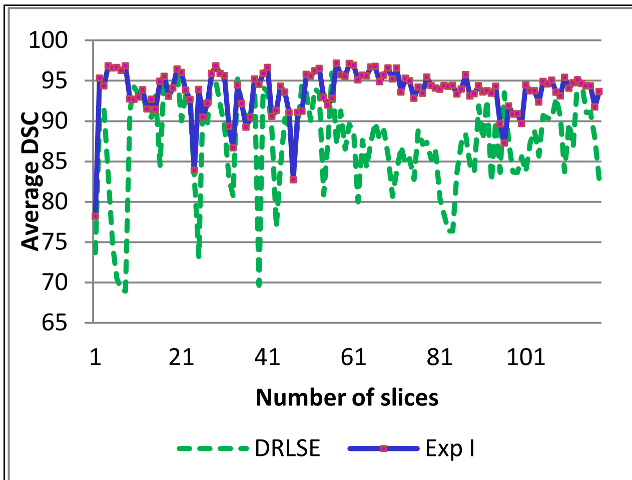
Fig.7.6 Comparative performance results of DRLSE and Experiment I on all test cases. Contour evolution using different methods is highlighted with red lines; over segmentation (leakage)

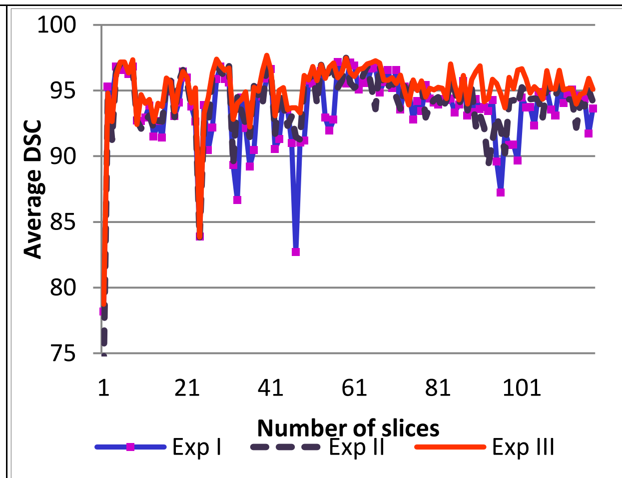
A: Test case 1 — 1: Tumor boundary extraction using DRLSE method

B: Test case 2 — 2: Tumor boundary extraction using experiment I

C: Test case 3

DRLSE method failed to evolve during contour evolution in convex structures and give distorted output at nearby edges and leaked to the adjacent liver area. As a result it leads to false edge detection and ended in preconvergence.





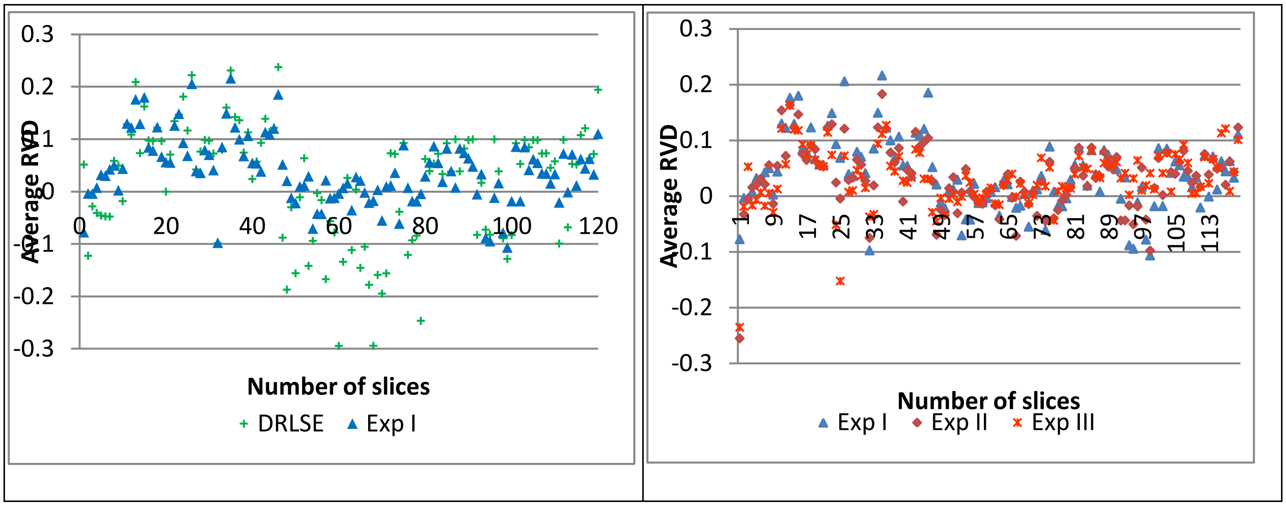
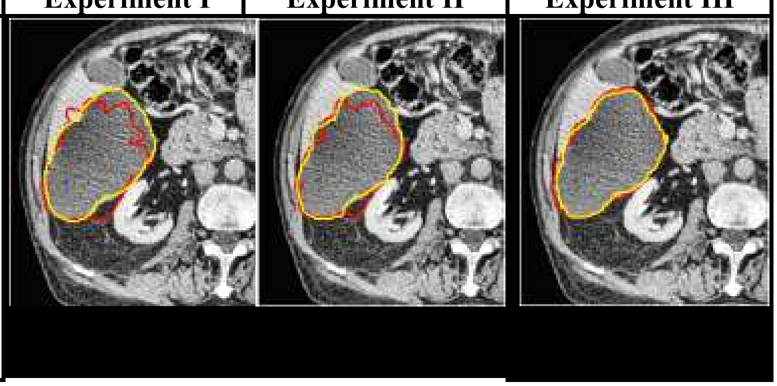


Fig.7.7 Segmentation results on test case #1. (A)results of average DSC using DRLSE and MDRLSE-experiment I methods(B) results of average DSC using MDRLSE-experiment I,II and III methods(C) results of average RVD using DRLSE and MDRLSE-experiment I methods(D)results of average RVD using MDRLSE-experiment I,II and III methods

Fig.7.7 shows that experiment I found superior to DRLSE method in terms of mean±SD of DSC and RVD values i) 89.11± 6.99% to 93.00±7.07% and 0.053 ±0.365 to 0.041±0.0647 in test case #1 ii) 81.4± 17.4% to 85.4±7.3% and -0.266± -0.299 to -0.098± 0.248 in test case #2 and iii) 83.6±3.9% to 90.6 ±1.6% and 0.289± 0.119 to 0.0658±0.087 in test case #3 respectively.

Experiment II: Template 4 used in MDRLSE experiment II method segment i) 30 tumors but show some leakage problem in test case #1 ii) Tumor segmentation accuracy increases in experiment II and segment 12 tumors successfully in test case #2 with no boundary leakage iii) 8 tumors out of 11 tumors in test case #3 but exhibit a problem in case of heterogeneous tumors with very low contrast with surrounding liver pixels.

	Modified DRLSE		
	Experiment I	**Experiment II**	**Experiment III**
Test case1			

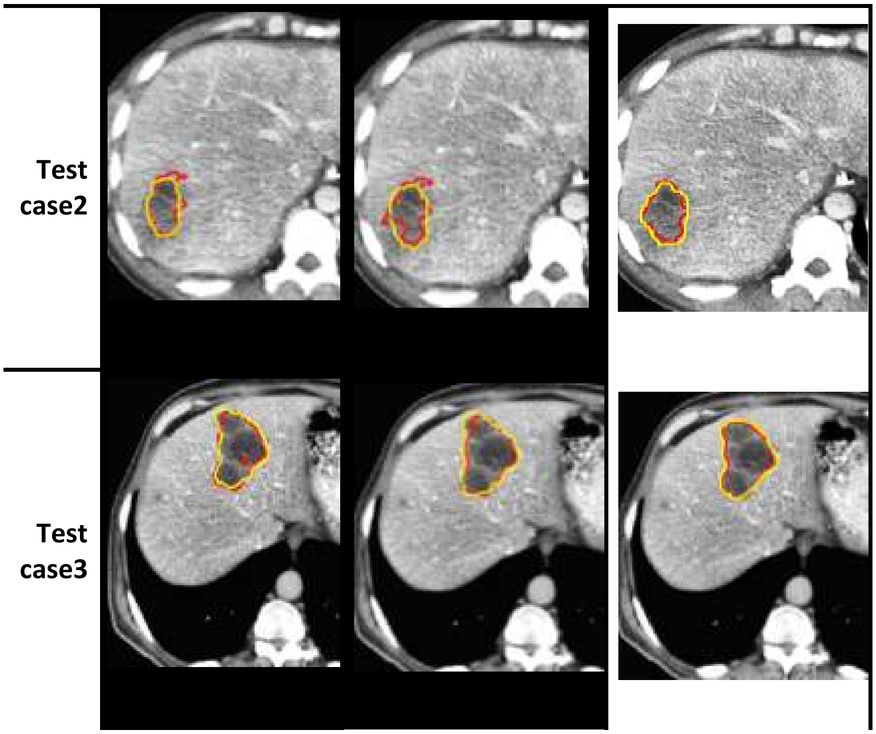


Fig.7.8 Comparative performance results of MDRLSE experiment I,II and III on all test cases. Contour evolution using different methods is highlighted with red lines; over segmentation (leakage)

A: Test case 1	1: Tumor boundary extraction using experiment I
B: Test case 2	2: Tumor boundary extraction using experiment II
C: Test case 3	3: Tumor boundary extraction using experiment III

Fig.7.8(column1 and 2) shows the comparison of Experiment II with experiment I on all three test cases which exhibit that over segmentation or leakage at the boundary of tumor has been decreased significantly with increase in template size. This fact is justified subjectively by comparative analysis of experiment I and II where mean± SD of DSC and RVD increases from i) 93.00±7.07% to 93.8± 9.02% and 0.041±0.0647 to 0.0333± 0.0608 in test case #1 ii) 85.4±7.3% to 85.7± 9%and -0.098± 0.248 to 0.0858 ±0.22259 in test case #2 and iii) 90.6 ±1.6% to 91.57±2.8% and 0.0658±0.087 to 0.0195 ± 0.059 in test case #3.

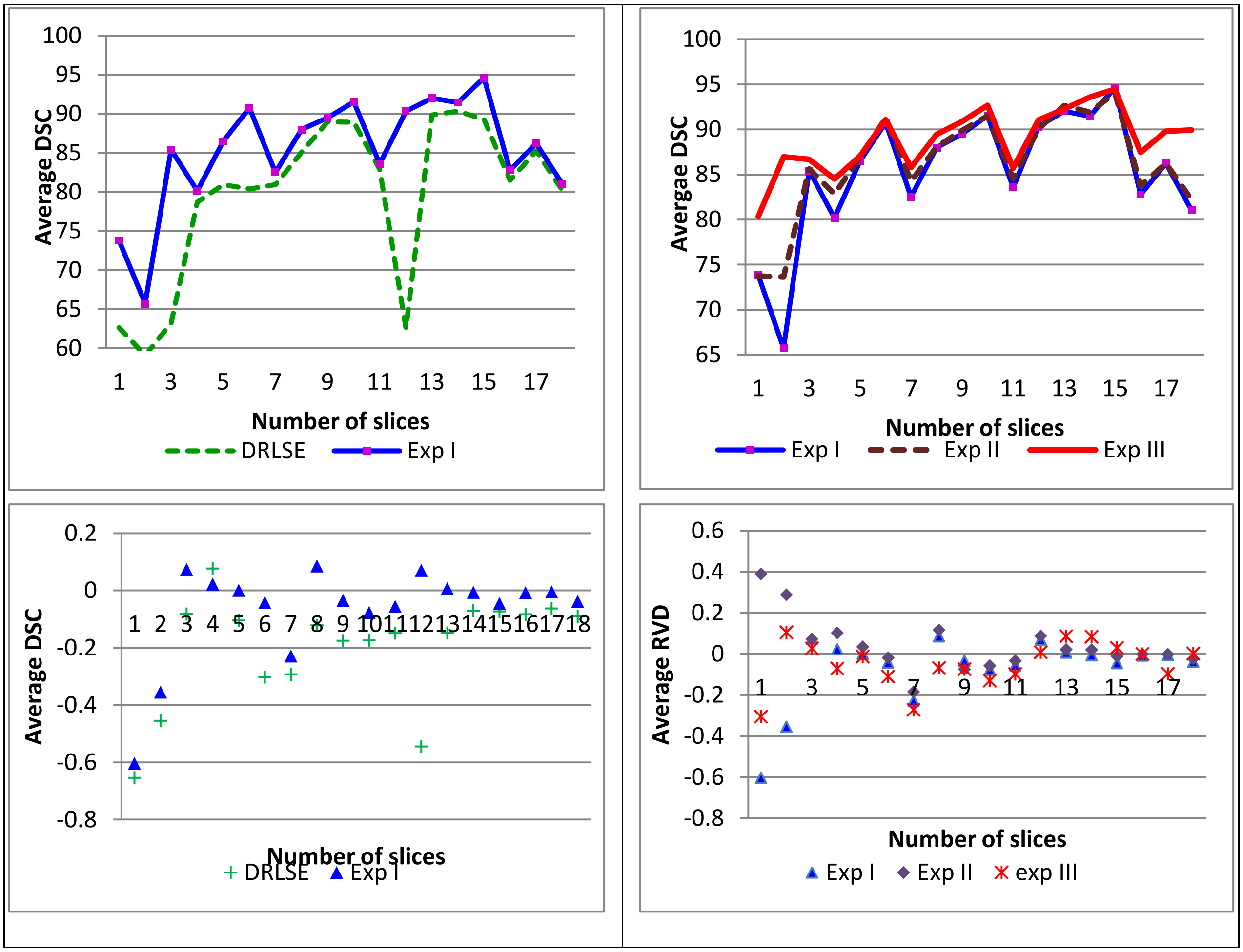


Fig.7.9 Segmentation results on test case #2. (A)results of average DSC using DRLSE and MDRLSE-experiment I methods(B) results of average DSC using MDRLSE-experiment I,II and III methods(C) results of average RVD using DRLSE and MDRLSE-experiment I methods(D)results of average RVD using MDRLSE-experiment I,II and III methods.

Experiment III: A template of 6 neighborhood pixels is used in third experiment to segment that low contrast and heterogeneous tumors. Third modification successfully segments most of the tumors in the dataset of patient with better convergence and overcome the problem of leakage or over segmentation and under segmentation.

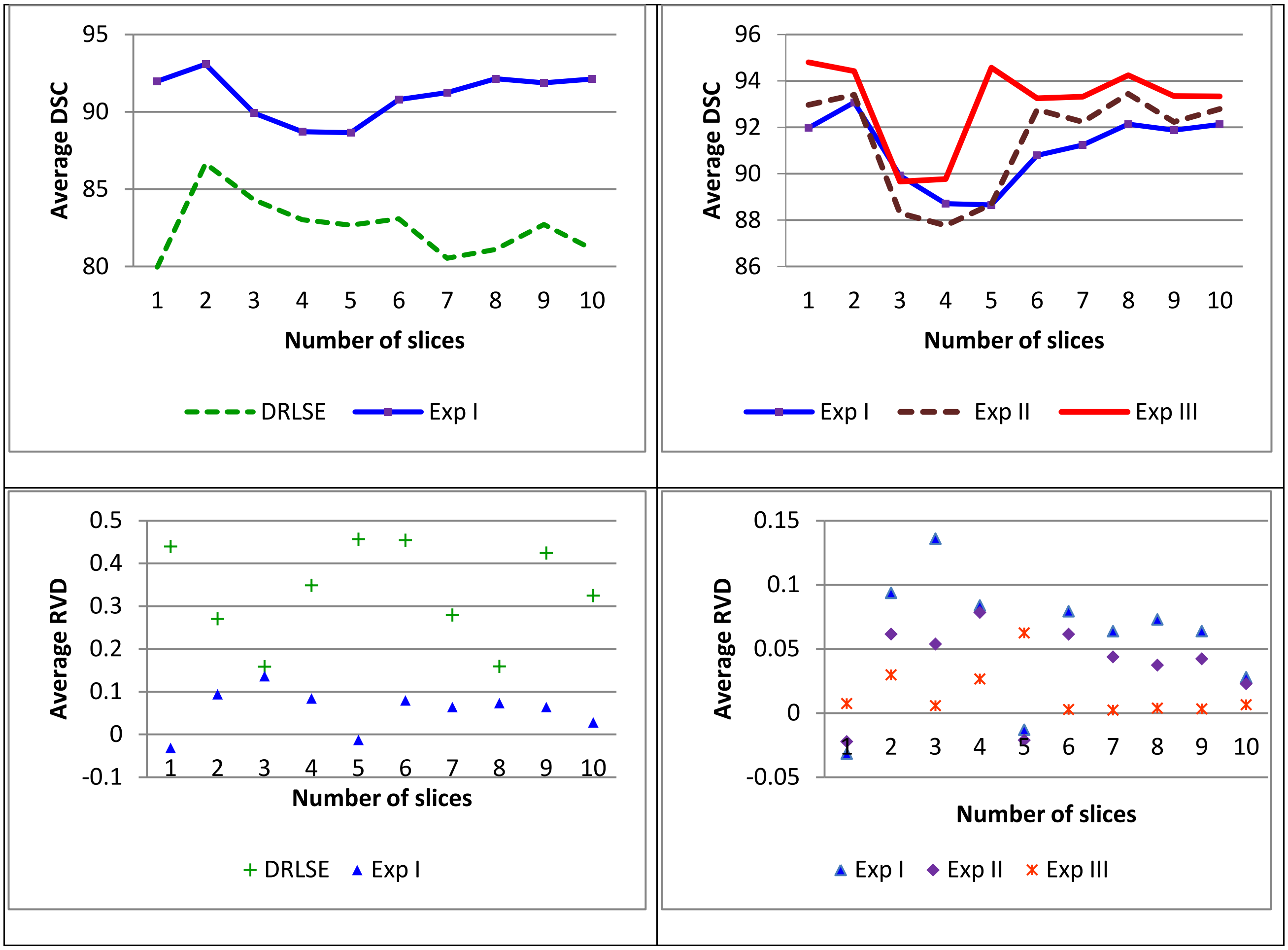


Fig.7.10 Segmentation results on test case #3. (A)results of average DSC using DRLSE and MDRLSE-experiment I methods(B) results of average DSC using MDRLSE-experiment I,II and III methods(C) results of average RVD using DRLSE and MDRLSE-experiment I methods(D)results of average RVD using MDRLSE-experiment I,II and III methods

Fig.7.8(column 2 and 3) shows the superiority of experiment III over II and exhibit that experiment III gives accurate segmentation results and overcome the problem of over segmentation where average values of DSC and RVD increases from i) 93.8± 9.02% to 94.8 ±7.8 and 0.0333± 0.0608 to 0.0347 ±0.0549in test case #1 ii) 85.7± 9% to 87.8 7.5% and 0.0858 ±0.22259 to 0.0967± 0.2218in test case #2 and iii) 91.57±2.8% to 92.67 ±2.86% and 0.0195 ± 0.059 to 0.0185± 0.0158in test case #3. Fig.7.9 shows the comparative analysis and from the graphical representation, it is clearly visualized that experiment II and III gave saturated and similar results for both DSC and RVD and therefore there is no need of further advancement of templates in stopping function.

The volume overlapping evaluated using DSC and its comparison depicts that in case of test case #1, average DSC range reached a highest value of 94.80 ±7.8 from 89.11± 6.99, test case #2 reached a higher average DSC of 92.96±2.86, whereas DRLSE provided an average DSC of 83.6±3.9 and in case of test case #3,average DSC improved from 81.4± 17.4 to 87.5 ±7.5.RVD gives the volume difference between ground truth and segmented result and its

.

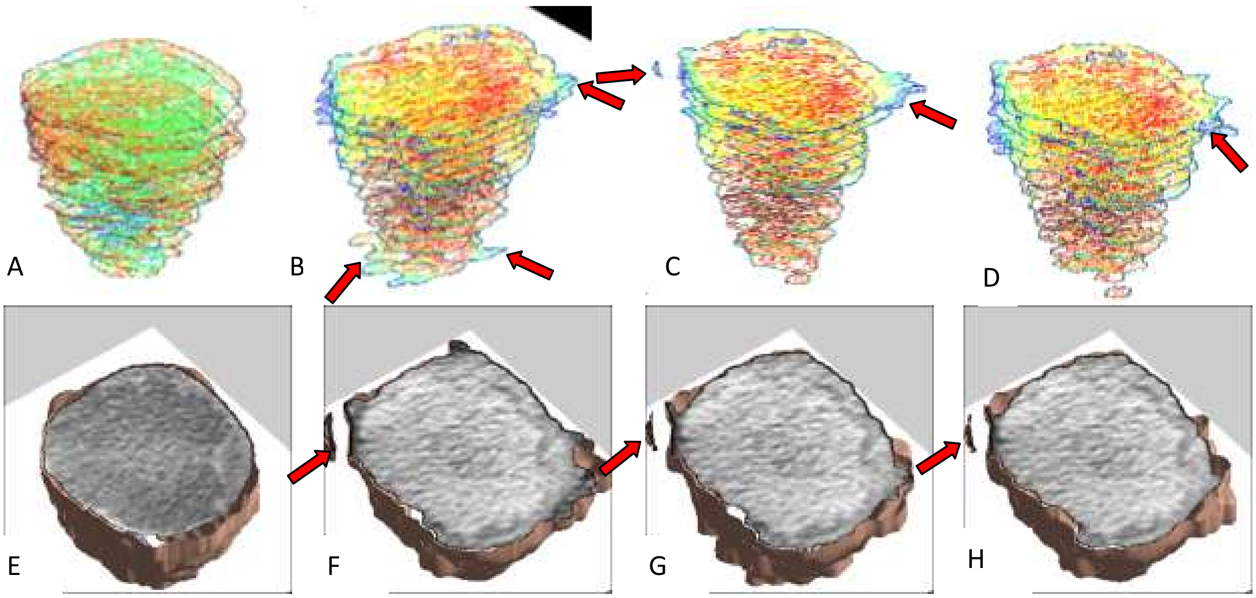


Fig.7.11 3D reconstruction from 2D CT image slices (Row 1)stacked 2D slices of tumors and complete volume(Row 2) by (A,E) manually segmented tumor image slices,(B,F) experiment 1with leakage at the boundary (C,G) experiment 2 with leakage at the boundary with some leakage in some cases(D,H) experiment 3. Red Arrow: leakage at the boundary in some tumor cases.

positive and negative values shows the deviation from true segmentation results. In test case #1, the average RVD values provided by DRLSE was 0.053 ±0.365 which reached a higher value of 0.0347 ±0.0549 in experiment III, which is nearer to true ground truth values. In test cases #2 and #3, DRLSE provided an average RVD of -0.266± -0.299, 0.289± 0.119 respectively, while experiment III reached an average value of 0.0967± 0.2218, 0.0185±0.0158 respectively. As discussed earlier in Section 1, 3D volume reconstructions is usually preferred for better analysis of liver disease diagnoses and follow up of liver cancer. In account of this, a comparative 3D volume reconstruction from 2D slices of CT tumor segmentation from manual segmentation as well as from three experiments is done which is shown in fig.7.11.

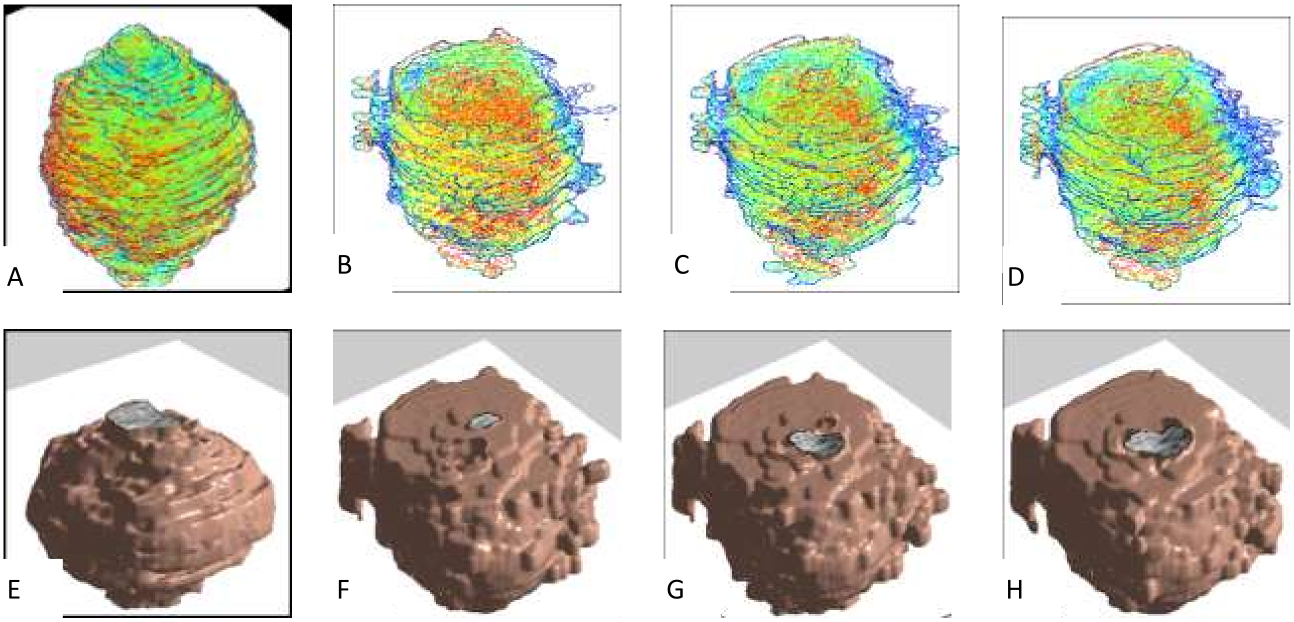


Fig.7.12 3D reconstruction from 2D CT image slices (Row 1)stacked 2D slices of tumors and complete volume(Row 2) by (A,E) manually segmented tumor image slices,(B,F) experiment 1with leakage at the boundary (C,G) experiment 2 with leakage at the boundary with some leakage in some cases(D,H) experiment 3.

2D contour slice of segmented tumor from test case #2 are stacked to form 3D volume of size 281x351x35. Fig. 7.11 (Row 1) shows the stacked contour slice plot of segmented hepatic tumor and Fig. 7.11(Row 2) shows the surface plot of hepatic tumor. Comparative study of all three volumes of tumor obtained from three experiments with respect to manual segmentation volume depicts that experiment 3 is very much in agreement with manual segmentation results. Fig. 7.12 shows the 3D reconstruction of all the tumors stacked together (row 1) and surface plot is shown in row 2.

7.2.3 Discussion:

Hepatic tumors have ambiguous boundaries and irregular shapes. Therefore tumor segmentation is a very crucial step in medical image analysis. The main objective of present work is to provide a flexible and comprehensive framework that can accurately segment different types of tumors. In the present work, DRLSE method is modified to overcome the drawback of level set method. Basic level set method employed on tumors encounter the problem of leakage and under segmentation in case of weak boundaries and in heterogeneous type of tumors. Modification in DRLSE method is done by applying templates of large size in place of central difference scheme employed in DRLSE to approximate spatial derivative. This in turn applied to calculate the gradient term of edge indicator function for better segmentation.

Qualitative analysis of modified method is done by comparing ground truth images marked by expert radiologist with segmented output of level set method. DRLSE method was tested on liver tumor images. But DRLSE method did not give satisfactory segmentation results in homogenous tumors with low contrast and in case of heterogeneous tumors. Exact boundary detection in tumor cases and to eliminate the leakage problem of level set method were the main objectives of MDRLSE method. By considering all these points DRLSE method was modified to MDRLSE method with increase in the size of template in forward difference scheme, the accurate detection of tumor boundaries increase with decrease in leakage of contour at weak edges. Out of all the experiments used in MDRLSE method experiment III with template 6 gives most accurate segmentation result. It is proved qualitatively and quantitavely.

Table 7.4: Comparisons of different segmentation results employed in recent year:

Year	Author	Method	DSC (%)
2008	Massoptier and Casciaro	• Active contour technique using gradient vector flow(GVF)	88.9
2012	Casciaro *et al.*	• Graph-cut algorithms • Active contour(GVF)	88.65 87.10
2009	Smeets *et al.*	• Level set method	83.7
2012	Li *et al.*	• Unified level set method	86.9
2016	-	• Proposed MDRLSE method	**94.8**

Qualitative results shown in fig.7.6, clearly shows the difference among DRLSE and three experiments. DSC and RVD give better results by improving DSC from i) 89 % to 94.8% in case of homogenous tumors ii)81.4% to 87.5% in case of heterogeneous tumors iii)83.6 % to 92.7% in case of multiple tumors with heterogeneity. These results are compared with previous methods and it is observed that DSC by employing MDRLSE method increases by a considerable amount as shown in fig. 7.7and 7.9. Furthermore, 3D volume reconstruction is done to extract exact volume of hepatic tumor. From above discussion, it is clear that by the choice of different templates the accuracy of tumor segmentation is increased considerably and it can be employed for the diagnosis of different cases of tumor in the liver.

CHAPTER 8
CONCLUSION

The comparative evaluation showed that active contour method provide superior results in comparison with level set method in the segmentation of liver tissues of uniform texture and intensity. The foremost drawback of active contour method is it requires user interaction by initially giving seed points in the image at the boundary of image. It consumes most of the processing time whereas level set method do not need user interaction. Level set method can split and merge in efficient way which is a inherent property of level set method. These advantages of level set method draw the attention for segmentation. Computerized hepatic tumor segmentation is a challenging task due to intratumoral heterogeneity and ambiguous boundaries. Distance regularized level set method proposed by Li *et al*. on CT images exhibit boundary leakage problems. The present work presented a modified distance regularized level set method which provides more robust and accurate segmentation of homogenous and heterogeneous tumors having weak edges and uneven texture. Proposed MDRLSE method proposed a gradient-based stopping function in which spatial derivative approximation in x and y direction is done by adding large number of neighborhood pixels. Performance measurement of proposed method is done qualitatively by comparison of ground truth images marked by expert radiologist and segmented CT images whereas quantitative evaluation is done by two evaluation metrics i.e. DSC and RVD. Tumor volumetry helps in better visualization and assessment of hepatic tumor. For future development in segmentation method, the main focus will be to develop an automatic segmentation method which can work on low contrast CT images with better tumor segmentation accuracy on heterogeneous tumors. The use of automatic initialization will reduce the computational time, user interaction and the segmentation will be less prone to inter and intra-user variability. Future work will also be focused on improved 3D volume construction of hepatic tumor with more smooth and detailed modeling of hepatic tumor surface.

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[1] R.Thakur, and D. Mittal, “Segmentation of Liver from Abdomen CT images and 3D Visualization,” Journal of Biomedical Engineering and Medical Imaging, vol. 2, pp.46-55, 2015.

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