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Medical Image Segmentation using CT Scans-A Level Set Approach

Sajith A. G., Hariharan S.

***Abstract*—. Identification of Liver and liver tumors from CT images is of great interest to physicians and image processing researchers. In this paper a simple and clinically useful system has been developed for segmenting the liver tumor from CT images. Level set methods have been widely used in image processing for segmenting the biomedical images such as liver images. Various methods of segmentation were explored, and a few were chosen for implementation and further development. Liver Images were collected and the region of interest was selected. Segmentation has been performed by using Fuzzy C means algorithm followed by fine delineation using level sets. The method could clearly segment the tumor regions and their boundaries are well defined.**

***Index Terms*—FCM, Level Set method, Liver tumors**

I. INTRODUCTION

Image segmentation [1, 2, 3] is an important step in image analysis process [4, 5, 6, 7]. Classical image segmentation methods [8, 9, 10] such as region growing, splitting and merging, thresholding etc have been extensively studied by researchers and several variations have been proposed. Almost all the segmentation methods have been developed and the images into different regions efficiently. However all the regions boundaries are marked in a similar way without giving much importance to the region of interest. In order to solve this problem in this work we first segment the region of image by using FCM and edges are well defined with the help of level set methods.

In this paper we focus on segmentation of liver tumor[11,12,13,14] from different CT images by using level set methods. Liver and liver tumor segmentations [15, 16, 17, 18] are very important for a contemporary planning [19, 20, 21] system of liver surgery[22,23,24]. Over the past few years level set methods were used for image segmentation. The idea of the level set method [25] is to be implicitly represented a contour or interface as the zero level set. The level set method is used as numerical technique for analysis of medical images. With the level set representation the image segmentation problem can be formulated and solved in a principled way based on well established mathematical theories, including calculus of variations and partial differential equations. An advantage of the level set method is that numerical computations involving curves and surfaces can be performed on a fixed Cartesian grid without having to parameterize these objects.

The remainder of this paper is organized as follows. In section II, Block schematic is explained.FCM method is introduced in Section III.Level set method is explained in Section IV and V.The implementation and results of our method are given in Section VI.

II. BLOCK DIAGRAM

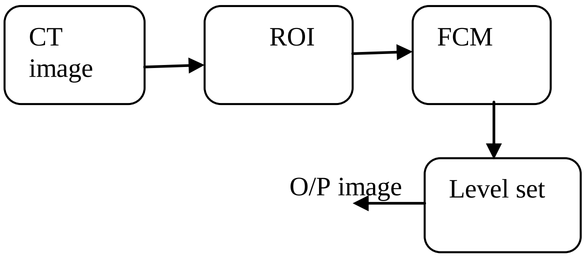

Fig.1 Proposed System

The image of the liver (ROI) is automatically extracted from CT images. A single threshold is used to extract liver from the CT images, segment the liver as a whole and is incapable to segment lesions present in the liver. Initially tumor region is extracted by using FCM; the initial segmentation by FCM may serve as the initial guess for level set evolution.

III. SEGMENTATION BY FCM

FCM has been widely utilized for medical image segmentation. FCM is a method of clustering which allows one piece of data which belongs to two or more clusters. FCM is used to segment the lesion from the extracted liver. The pixels of the input image are divided into three clusters. The first cluster includes pixels in the background. The second cluster includes pixels in the liver other than lesion and the third cluster includes pixels in the lesion.

The objective function of FCM is

$$J=\sum_{j=1}^{N}\sum_{i=1}^{c}\mu_{ij}^{m}\left\|x_j-v_i\right\|^2 \qquad (1)$$

where μ_{ij} represents the membership of pixel x_j in the ith cluster, v_i is the ith cluster center and m is a constant controlling the fuzziness of the resulting segmentation. The membership functions are subject to the constraints

$$\sum_{i=1}^{c}\mu_{ij}=1, 0\le\mu_{ij}\le 1 and \sum_{j=1}^{N}\mu_{ij} \qquad (2)$$

The membership functions μ_{ij} and the centroid v_i are given by

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Sajith A.G, Electrical & Electronics, Sarabhai Institute of Science and Technology, Kerala, India.
Hariharan S, Electrical & Electronics, College of Engineering, Kerala, India.

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$$\mu_{ij} = \frac{\left\| x_j - v_i \right\|^{-2/(m-1)}}{\sum_{k=1}^{c} \left\| x_j - v_k \right\|^{-2/(m-1)}} \quad (3)$$

$$v_i = \frac{\sum_{j=1}^{N} \mu_{ij}^{m} x_j}{\sum_{j=1}^{N} \mu_{ij}^{m}} \quad (4)$$

The system is optimized when the pixels close to their cluster's centroid are assigned high membership values, and low membership values are assigned to the pixels far away from the centroid.

IV. TUMOR DELINEATION BY LEVEL SET METHOD

The idea of the Level set method is to be implicitly represented a contour or interface as the zero level set of a higher dimensional function, called the level set function, and formulate the evolution of the contour through the evolution of the level set function. In this paper it is desired to detect and delineate liver tumors in CT scans by using level set model. This technique is very suitable for medical organ segmentation since it can handle any of the cavities, concavities, convolutedness, splitting or merging. Another benefit of this technique is that this algorithm increases the capture range[26,27,28] of the field flow. Level set is a deformable contour model where the user specifies a starting contour that is evolved to the image contour; the level set method is a geometric deformable model. The contour is described as a surface developed by partial differential equations[29,30], where the contour is the zero level of the surface. The partial differential eqn. can then be written as

$$\frac{\partial \phi}{\partial t} = -\left| -\nabla \phi \right| .F \quad (5)$$

which is called the level set eqn. and where the symbol ϕ denotes the level set function. In the above level set eqn. F is the velocity term that describes the level set evolution. By manipulating F, we can guide the level set to different areas or shapes, given a particular initialization of the level set function. F may also be dependent on an edge indicator function, which is defined as having a value zero on an edge, nd non-zero otherwise. This causes F to slow the level set evolution when on an edge. The level set method proposed by Osher and Sethian is a versatile tool for tracing the interfaces that may separate an image Ω into different parts. The main idea behind it is to characterize the interface function $\Gamma(t)$ by a Lipchitz function ø,

$$\begin{Bmatrix} \phi(t,x,y) > 0 (x,y) \text{ is inside } \Gamma(t) \\ \phi(t,x,y) = 0 (x,y) \text{ is at } \Gamma(t) \\ \phi(t,x,y) < 0 (x,y) \text{ is outside } \Gamma(t) \end{Bmatrix} \quad (6)$$

In this paper the evolution equation used is

$$\frac{\partial \phi}{\partial t} = \mu \left[\nabla \phi - div\left(\frac{\nabla \Phi}{|\nabla \phi|}\right) \right] + \lambda \delta(\phi) div\left(g \frac{\nabla \Phi}{|\nabla \Phi|}\right) + \gamma g \delta(\Phi) \quad (7)$$

The second and the third term in the right hand side of eqn. correspond to the gradient flows of the energy functional $\lambda L_g(\Phi) and \gamma A_g(\Phi)$, respectively, where

$$L_g(\Phi) = \int_{\Omega} g\delta(\Phi)|\nabla \Phi| dxdy \quad (8)$$

and

$$A_g(\Phi) = \int_{\Omega} gH(-\Phi)dxdy \quad (9)$$

where δ is the univariate Dirac function, and H is the Heaviside function.These terms are responsible of driving the zero level curve towards the object boundaries. To explain the effect of the first term, which is associated to the internal energy µP (ø), we notice that the gradient flow

$$\nabla \phi - div\left(\frac{\nabla \Phi}{|\nabla \phi|}\right) = div\left[\left(1 - \frac{1}{|\nabla \Phi|} \right) \nabla \Phi \right] \quad (10)$$

has the factor $\left(1 - \frac{1}{|\nabla \Phi|} \right)$ as diffusion rate. If $\nabla \Phi$ >1, the diffusion rate is positive and the effect of this term is the usual diffusion. If $\nabla \Phi$ <1, the term has effect of reverse diffusion and therefore increase gradient.

V. INITIALIZATION OF LEVEL SET FUNCTION

Level set formulation consists of three partial differential equations, one of which is introduced to restrict the level set function to be a signed distance function, and the other two of which are described the motion of the zero level contour. In the present work, we propose a variational level set formulation with an intrinsic mechanism of maintaining the signed distance property of the level set function. The mechanism is associated with a penalty term in the variational formulation that penalizes the deviation of the level set function from a signed distance function. The penalty term not only eliminates the need for reinitialization, but also allows the use of a simpler and more efficient numerical scheme in the implementation than those used for conventional level set formulation. In this method not only the re-initialization procedure is completely eliminated but also the level set function ø is no longer required to be initialized as a signed distance function. Here the region based on initialization of level set function is used which is computationally efficient and allows for flexibility in some situations. The proposed initial level set functions are computed from an arbitrary region Ω_0 in the image domain Ω. For example, if the region of interest can be roughly and automatically obtained in some way, such as thresholding, and then we can use these roughly obtained regions as the regions Ω_0 to construct the initial level set function Φ_0 . Then the initial level set function will evolve in an uniform fashion according to the evolution of equations and level set curves converged to the region of interest. The initial level sets may be simply defined as

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$$\phi_o = \begin{Bmatrix} -c & if\ (x,y)\ is\ inside\ \Omega_0 \\ +c & otherwise \end{Bmatrix} \tag{11}$$

where c should be a constant larger than ε, where ε is an energy function.

VI. IMPLEMENTATION

The Dirac function $\delta(x)$ in (6) is slightly smoothed as the following function $\delta_e(x)$,defined by

$$\delta_e(x) = \begin{Bmatrix} 0 & if\ |x| > \varepsilon \\ \frac{1}{2\varepsilon}\left[1+\cos\left(\frac{\Pi x}{\varepsilon}\right)\right] & if\ |x| \le \varepsilon \end{Bmatrix} \tag{12}$$

All the partial derivatives $\frac{\partial\Phi}{\partial x}$ and $\frac{\partial\Phi}{\partial y}$ are approximated by the central difference, and the temperoal partial derivative $\frac{\partial\Phi}{\partial t}$ is approximated by the forward difference. The approximation of (6) by the above difference scheme can be simply written as

$$\frac{\Phi_{i,j}^{k+1} - \Phi_{i,j}^{k}}{\tau} = L(\Phi_{i,j}^{k}) \tag{13}$$

where $L(\Phi_{i,j}^{k})$ is the approximation of the right hand side in (6) by the above spatial difference scheme.

VII. RESULTS AND DISCUSSIONS

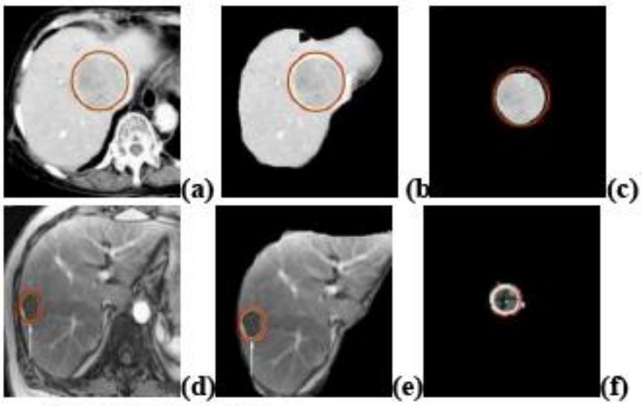

Fig.2. Non cancerous

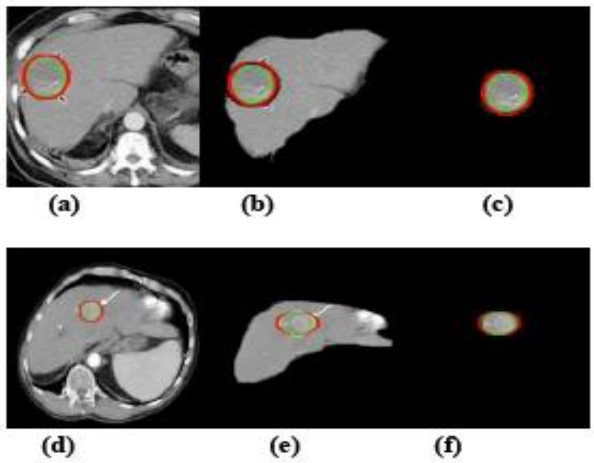

Figure.3 Cancerous

Fig (4)Original CT image(Benign tumor)

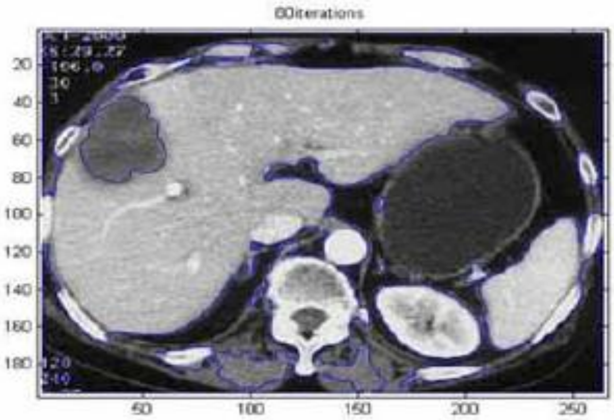

Fig.(5).Segmented image of fig(4) with 80 iterations (Benign tumor).

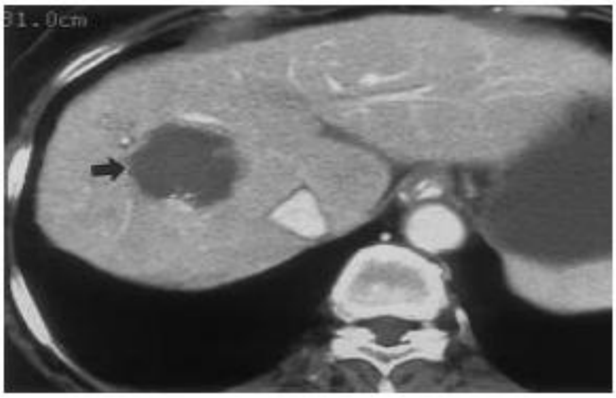

Fig.(6).Original CT image (Benign tumor)

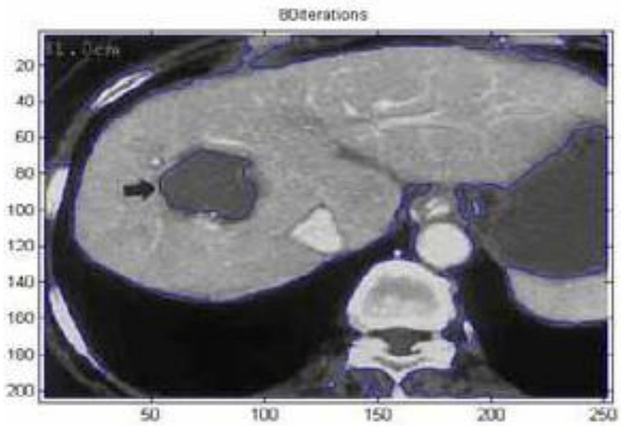

Fig.(7).Segmented image of fig(6) with 80 iterations(Benign tumor)

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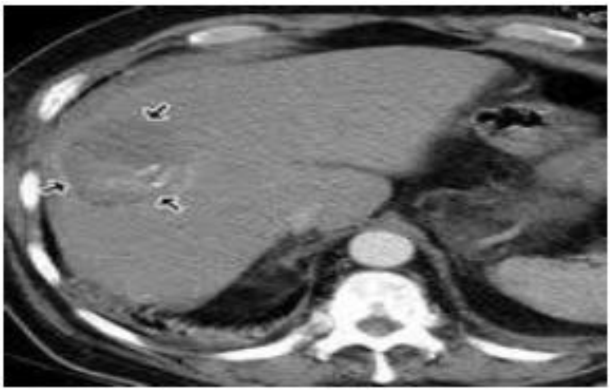

Fig (8).Original CT image (Malignant tumor)

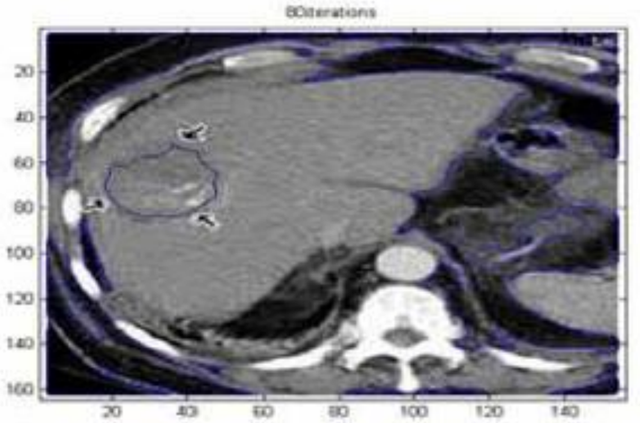

Fig (9).Segmented image of fig(8) with 80 iterations (Malignant tumor)

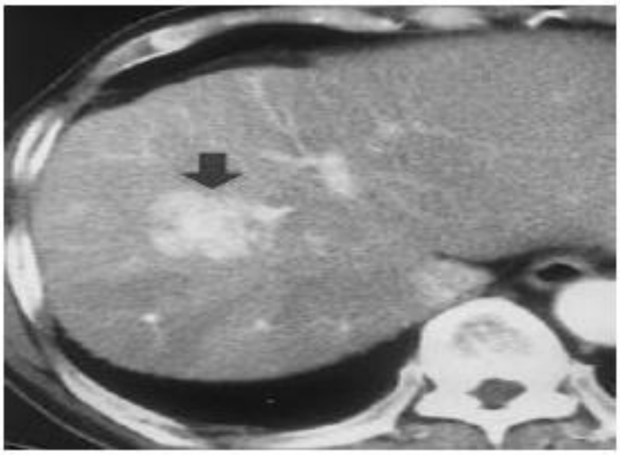

Fig (10).Original CT image (Malignant tumor)

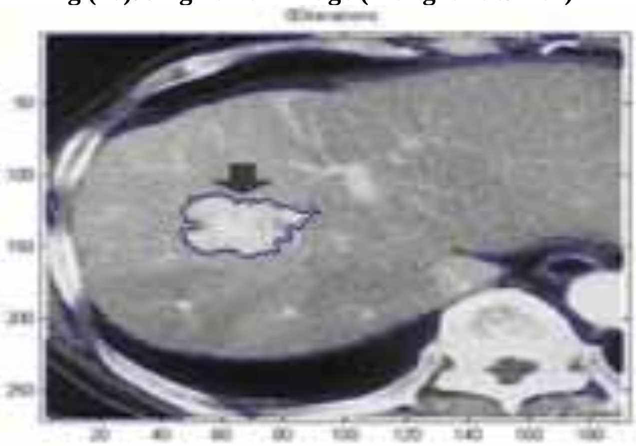

Fig (11).Segmented image of fig(10) with 80 iterations(Malignant tumor)

Liver tumor segmentation on CT images is a challenging problem**.** In liver there are different types of abnormalities present, such as benign, malignant, liver metastases, cirrhosis etc.Tumors can be benign, lacking the capacity to spread to other organs, or malignant. The malignant tumor display uncontrollable growth and may invade and destroy healthy surrounding tissue. Hence decision making whether surgery is needed or not is a very difficult question in medical arena. Surgery to remove the deceased part of the liver is the main and most effective treatment for primary liver tumors.

In this paper a method is developed to segment the liver and fine delineation is done using level set method. Various malignant and benign tumors are collected and they are segmented and delineated using level set method. Tumor parts are properly segmented and the output images are analysed.Non cancerous images are shown in fig(2),fig(4)and fig(6). Cancerous images are shown in fig(3),fig(8) and fig(10).They are segmented and fine delineation of tumors are done in the CT images and shown in fig(5),fig(7),fig(9) and fig(11).

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AUTHORS PROFILE

Sajith A.G., received the M.Tech degree in electrical and electronics engineering from College of Engineering,Trivandrum,Kerala, India, in 2010.His current research interests include variational methods for medical image processing and efficient algorithms to solve them.

Hariharan S., received the M.Tech degree in biomedical engineering from IIT Bombay,India,in 1992 and the Ph.D. degree in electrical engineering from IIT Kharagpur, India, in 2003.He has got many National and International publications. His current research interests include variational methods for medical image processing and efficient algorithms to solve them.