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A Fast Level Set Algorithm for Liver Tumor Segmentation

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Abstract— Accurate and fast image segmentation algorithm is of paramount importance for a wide range of medical imaging applications. The most widely used image segmentation algorithms are region based and typically rely on the homogeneity of the image intensities in the regions of interest, which often fail to provide accurate segmentation results due to the gradient function gives very small values at the boundary and makes the speed of the moving contour low and the gradient based term can never stop the level set evolution completely even for ideal edges, making leakage often inevitable. In this paper a fast narrow band distance preserving level set evolution algorithm is used for liver tumor segmentation. Experimental result for CT images shows desirable performances of the method.

Index Terms—Level set, FCM.

I. INTRODUCTION

During the last two decades, the necessity for biopsy of liver lesions has diminished. Most benign and many malignant lesions now are correctly diagnosed noninvasively with either computer tomography(CT) or magnetic resonance(MR) imaging, The term “image science” (or imaging science) is popular for denoting a wide range of problems related to digital images including medical images. It is generally refereed to problems related to image processing, computer graphics, and computer vision. The level set method [1, 2, 3, 4]for capturing moving fronts was introduced by Osher and Sethian in 1987[5,6]. Over the years it has proven to be a robust device for image processing field. Level set methods are extended for the use of Medical image segmentation, which usually refers to some PDE methods.

In the present work a medical diagnosis system for liver tumor segmentation based on a fast distance preserving narrow band level set evolution method[7,8,9] is used which is based on the variational level set formulation. 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 fast distance preserving narrow band level set evolution method. This method ensuring stable level set evolution, accurate computation and faster than most distance preserving LSM algorithms for medical image segmentation problem[10,11,12]. This method inherits all the advantages of the variational level set method [13, 14, 15], but significantly reduces the computation cost at each iteration.

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This paper is organized as follows. In section II Block schematic is explained.FCM method is explained in Section III.Section IV presents the introduction to level sets and the evolution equation.
The narrow band level set method is introduced in Section V. Implementation technique is discussed in SectionVI.The results are discussed in Section VII.

II. BLOCK DIAGRAM

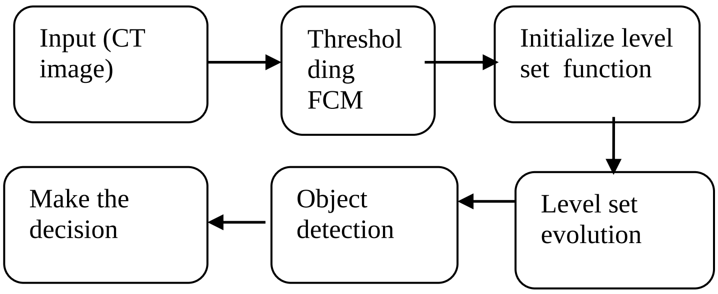

Fig.1 Proposed system

The outline of our proposed medical system is shown in Fig(1).This outline heavily carries the characteristics of a typical medical image segmentation 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. Final contour of the level set method gives the decision about the image object.

III. SEGMENTATION BY FCM

FCM has been widely utilized for medical image segmentation. FCM [16] 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

$$J=\sum_{k=1}^{n}\sum_{i=1}^{c}(u_{ik})^{q}d^{2}(x_k,v_i) \qquad (1)$$

Where “n” is the number of data items,”c” is the number of clusters with $2\leq c\leq n$,u_{ik} is the degree of membership of x_k in the i^{th} cluster,q is a weighting exponent on each fuzzy membership,v_i is the prototype of the centre of cluster i,$d^2(x_k,v_i)$ is a distance measure between object x_k and cluster centre v_i.
The membership functions u_{ik} and the centroid v_i are given by

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$$u_{ik}=\frac{1}{\sum_{j=1}^{c}\left(\frac{d_{ik}}{d_{jk}}\right)^{\frac{2}{q-1}}} \tag{2}$$

$$v_i=\frac{\sum_{k=1}^{n}(u_{ik})^q x_k}{\sum_{k=1}^{n}(u_{jk})^q} \tag{3}$$

IV. AN OVERVIEW OF LEVEL SET METHOD

The level set method proposed by Osher and sethian is a versatile tool for tracing the interfaces that may separate an image into different parts. The main idea behind it is to characterize the interface functionΓ(t) by a Lipchitz function Φ, have the following properties

$$\left\{\begin{array}{l}\phi(t,x,y)>0(x,y)\ is\, inside\,\Gamma(t)\\ \phi(t,x,y)=0(x,y)\,is\,at\,\Gamma(t)\\ \phi(t,x,y)<0(x,y)\,is\,outside\,\Gamma(t)\end{array}\right\} \tag{4}$$

The interface Γ(t) is implicitly moved according to the nonlinear PDE

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

Where F is a given velocity field. This vector can be depending on geometry, position, time and internal or external parameters.

V. TUMOR DELINEATION BY LEVEL SET METHOD

The proposed initial level set functions are computed from an arbitrary region in the image domain Ω.The region of interest can be roughly and automatically obtained using fuzzy c-means clustering method and then we can use these roughly obtained regions to construct the initial level set function Φ_0. The energy term defined is

$$E\ =kE_{\text{int}}+E_{ext} \tag{6}$$

Where the parameter k is controlling the penalization effect of the internal energy.

$$E_{\text{int}}=\int_{\Omega}\frac{1}{2}\left(|\nabla\phi|-1\right)^2 dxdy \tag{7}$$

$$\begin{aligned}E_{ext}&=\mu.length\{c\}+\gamma.Area\{inside(c)\}\\&\quad+\lambda_1 M_{inside(c)}+\lambda_2 M_{outside(c)}\end{aligned} \tag{8}$$

Where C is the evolving curve and $\mu\geq 0$, $\Upsilon\geq 0$,$\lambda_1>0$ and $\lambda_2>0$ are the constraints.

The energy term in equation (6) can be rewritten as

$$\begin{aligned}E(\phi)\ &=\int_{\Omega}\frac{1}{2}\left(|\nabla\phi|-1\right)^2 dxdy\\&+\int_{\Omega}\delta(\phi)|\nabla\phi|\,dxdy\\&+\gamma\int_{\Omega}H(\phi)\,dxdy\\&+\lambda_1\int_{\Omega}|u_0-c_1|^2 H(\phi)\,dxdy\\&+\lambda_2\int_{\Omega}|u_0-c_2|^2\left(1-H(\phi)\right)dxdy\end{aligned} \tag{9}$$

$$\frac{\partial\phi}{\partial t}=-\frac{\partial E}{\partial\phi}=k.\left[\Delta\phi-div\left(\frac{\nabla\phi}{|\nabla\phi|}\right)\right]$$
$$+\delta(\phi)\left[\mu.div\left(\frac{\nabla\phi}{|\nabla\phi|}\right)-\gamma-\lambda_1.(u_0-c_1)^2-\lambda_2.(u_0-c_2)^2\right]^2$$
(10)

VI. IMPLEMENTATION

The proposed initial level set functions are computed from an arbitrary region Ωo 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 Ωo to construct the initial level set function Φo. 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

$$\Phi_0=\left\{\begin{array}{ll}-c & if\ (x,y)\ is\,inside\,\Omega_0\\ +c & otherwise\end{array}\right\} \tag{11}$$

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

For implementation Dirac function $\delta_\varepsilon(x)$ and Heaviside function $H_\varepsilon(x)$ is regularized as

$$H_\varepsilon(x)=\frac{1}{2}\left[1+\frac{2}{\pi}\arctan\left(\frac{x}{\varepsilon}\right)\right] \tag{12}$$

$$\delta_\varepsilon(x)=\left\{\begin{array}{ll}0 & if\ |x|>\varepsilon\\ \frac{1}{2\varepsilon}\left[1+\cos\left(\frac{\pi x}{\varepsilon}\right)\right] & if\ |x|\leq\varepsilon\end{array}\right\} \tag{13}$$

All the partial derivatives $\frac{\partial\emptyset}{\partial x}$ and $\frac{\partial\emptyset}{\partial y}$ are approximated by the central difference, and the temporal partial derivative $\frac{\partial\emptyset}{\partial t}$ is approximated by the forward difference. The approximation can be simply written as

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

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$$\Phi_{i,j}^{k+1} = \Phi_{i,j}^{k} + \tau L\left(\Phi_{i,j}^{k}\right) \qquad (14)$$

VII. RESULTS AND DISCUSSION

CT is a standardized procedure for the detection and characterization of a large variety of benign and malignant liver lesions. This helps in the decline of mortality and morbidity rates among patients with liver disease. CT scan is good non-invasive tool and can be used as first live imaging modality for differentiating benign and malignant focal liver lesions. Benign lesions like hemangioma can be reliably differentiated from malignant liver lesion, therefore unnecessary biopsies can be avoided. CT is the most sensitive technique for the detection of liver metastases(80-90% sensitivity and 99% specificity for contrast enhanced scans).The narrow band algorithm was tested on two sets of benign and malignant liver tumor CT images.

Fig.2.Benign tumor (a)

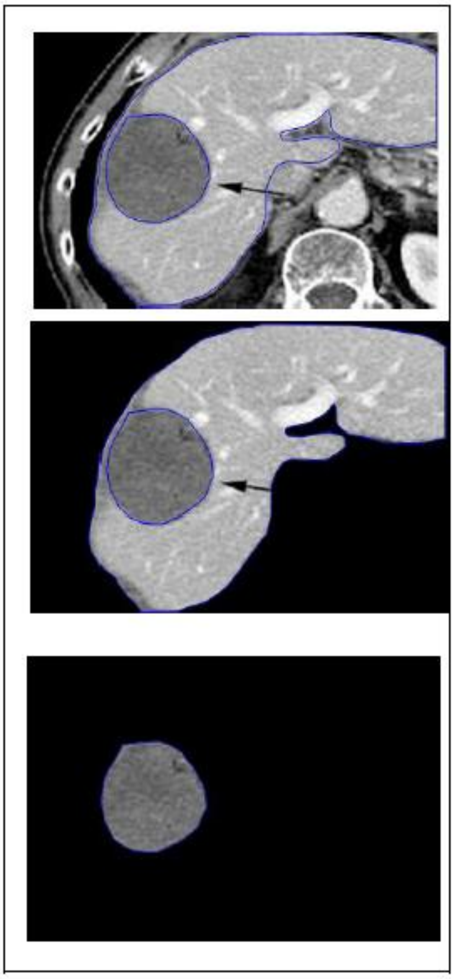

Fig.3.Benign tumor (b)

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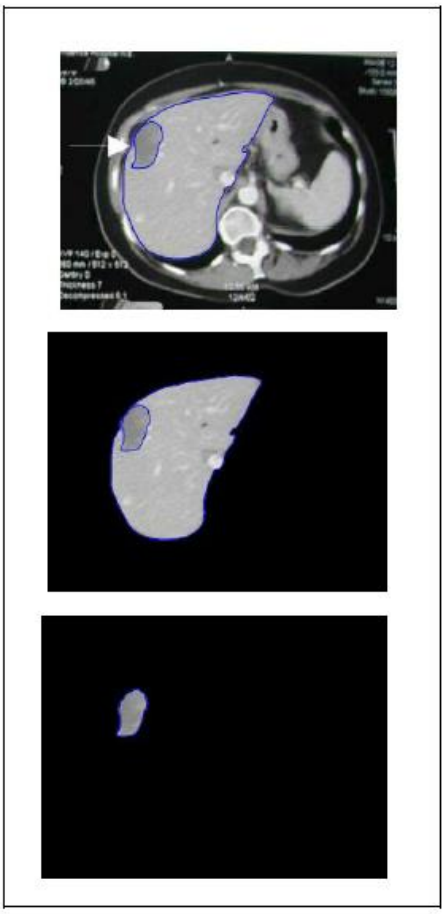

Fig.4.Malignant tumor (a)

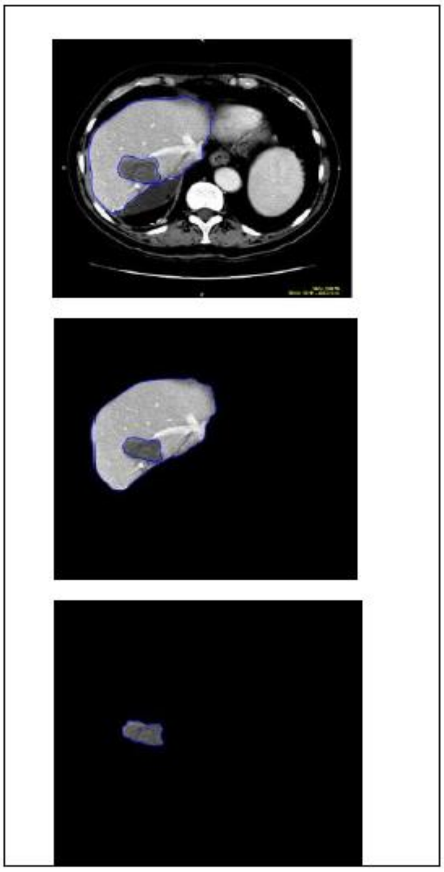

Fig.(5).Malignant tumor (b)

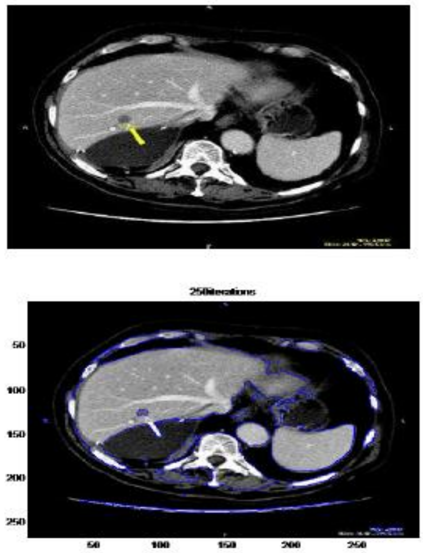

Fig.6.Benign tumor (a)

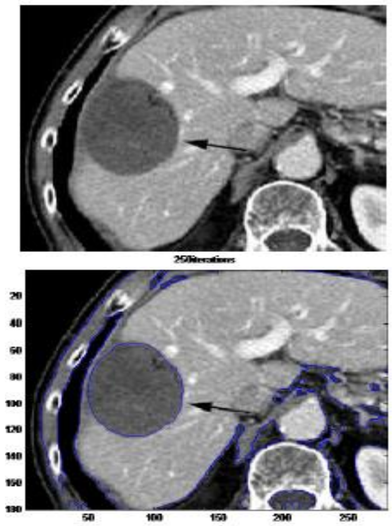

Fig.(7).Benign tumor (b)

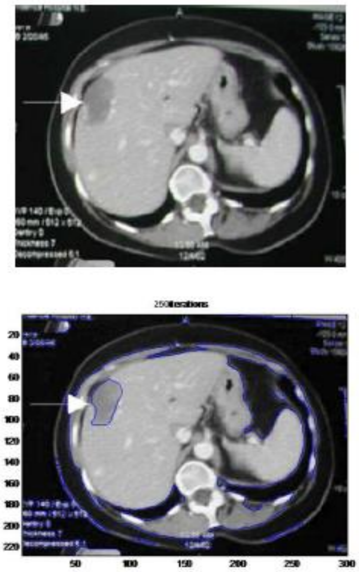

Fig.(8).Malignant tumor(a)

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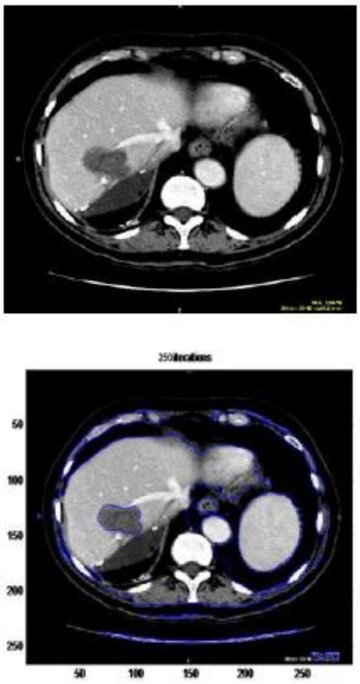

Fig.(9).Malignant tumor(b)

We first show the results for two sets of Benign liver tumor CT images in fig(2),fig(3) and Malignant liver tumor images in fig(4),fig(5). Liver with benign tumor and benign tumor are separated in second and third rows of fig(2) and fig(3). Liver with malignant tumor and malignant tumor are separated in second and third rows of fig(4) and fig(5).Narrow band evaluation is applied to the first row of Benign liver tumor CT images of Fig(6) and fig(7) and the results obtained are shown in the second row of fig(6) and fig(7). Narrow band evaluation is applied to the first row of Malignant liver tumor CT images of Fig(8) and fig(9) and the results obtained are shown in the second row of fig(8) and fig(9).This method successfully extracts the object boundaries for these four images.

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