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A Region based Active Contour Approach for Liver CT Image Analysis Driven by Local likelihood Image Fitting Energy

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Abstract: ***Computer tomography images are widely used in the diagnosis of liver tumor analysis because of its faster acquisition and compatibility with most life support devices. Accurate image segmentation is very sensitive in the field of medical image analysis. Active contours plays an important role in the area of medical image analysis. It constitute a powerful energy minimization criteria for image segmentation. This paper presents a region based active contour model for liver CT image segmentation based on variational level set formulation driven by local likelihood image fitting energy. The neigh bouring intensities of image pixels are described in terms of Gaussian distribution. The mean and variances of intensities in the energy functional can be estimated during the energy minimization process. The updation of mean and variance guide the contour evolving toward tumor boundaries. Also this model has been compared with different active active contour models. Our results shows that the presented model achieves superior performance in CT liver image segmentation.***

Index Terms: Active Contours, Chan-Vese model, Level sets

I. INTRODUCTION

Active Contours plays an important role in the field of medical image segmentation. Liver tumor segmentation in CT images is a key problem in medical image processing scenario. The goal is to exact separation of the tumor regions from the background organs inorder to visualize and analyze the physicians to predict the benign and malignancy conditions .Active contour model proposed by Kass et al. [1], has been proved to be an efficient framework for image segmentation. These models can be formulated under an energy minimization framework based on the theory of curve evolution. The solutions to these models can be obtained by using the level set method [2], whose basic idea is to represent a contour or surface as the zero level set of an implicit function defined in a higher dimension, and to formulate the motion of the contour or surface as the evolution of the level set function. The main advantage of this method is to handle the topological changes automatically. Active contour models can be generally categorized into two groups : the edge-based models[3-8] and region-based models [9-18]. Edge-based active contour models utilize local image gradients to attract contours toward object boundaries, whereas region-based models employ global image information in each region, such as the distribution of intensities, colors, textures and motion , to move contours toward the boundaries. In the field of medical image segmentation, we use an energy functional from a mathematical model and minimizing this energy functional to track the tumor regions. The popular piece- wise constant (PC) model is a typical variational level set method, which aims to minimize the Mumford_Shah functional .This model makes use of inside and outside regions global image properties with reference to the evolving curve into their energy functional as constraints. The PC model fails to segment the intensity inhomogenity images because it assumes that the intensities in each region always maintain constant.

Li et al.[13, 19] proposed an implicit active contours model based on local binary fitting energy, which used the local information as constraint, and works very well on the images with intensity inhomogeneities . This model outperformed both PC and PS models in segmentation accuracy and computational efficiency. Wang et al. [20] employed Gaussian distributions to model local image information, and proposed local Gaussian distribution fitting (LGDF) energy. Zhang et al. proposed a novel region-based active contour model for image segmentation, which combined the merits of the traditional GAC and PC models [21]. Zhang et al. exploited local image region statistics to present a level set method for segmenting images with intensity inhomogeneity . This model utilize a Gaussian filtering scheme to regularize the level set function. The LIF model can achieve similar segmentation accuracy to the LBF model with less computational costs .He et al. proposed an improved region-scalable fitting model based on the “modifying” kernel and local entropy . Two piecewise smooth (PS) active contour models [17] were developed under the framework of minimizing the Mumford–Shah functional[22] .Local intensity criteria has been extensively used in active contour models to improve the tumor boundary accuracy for the images corrupted by noise and intensity inhomogenity. In this paper we makes use of the image intensities within the neighborhood of each pixel to construct a image fitting energy functional, and is implemented this functional using variational level set formulation for image segmentation. The neighborhood regions can be partitioned into disjoint set and the local intensities in each region follows. The Gaussian distribution with variation in mean and variance.

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Based on the likelihood function of local intensity functional a local energy is defined and integrated over the entire image domain to form the local likelihood image fitting energy functional. This functional is implemented using the variational level set formulation with a regularized term. The information of CT image intensities is utilized to compute the means and variances for minimizing the energy functional inorder to attract the contour towards the tumor regions. The presented model has been compared with different active contour models.

II. ACTIVE CONTOUR MODELS

A. The Chan-Vese Model

Chan and Vese proposed an ACM which can be seen as a special case of the Munford-Shah problem, for a given image I in domain Ω, the C-V model is formulated by minimizing the following energy functional:

$$E^{CV} = \lambda_1 \int_{inside(C)} |I(x)-c_1|^2 dx + \lambda_2 \int_{outside(C)} |I(x)-c_2|^2 dx, \quad x \in \Omega \qquad (1)$$

where c_1 and c_2 are two constants which are the average intensities inside and outside the contour, respectively. With the level set method, we assume

$$C = \{x \in \Omega : \phi(x) = 0\}$$
$$inside(C) = \{x \in \Omega : \phi(x) > 0\}$$
$$outside(C) = \{x \in \Omega : \phi(x) < 0\}$$

By minimizing Eq.(1), we solve c_1 and c_2 as follows:

$$c_1(\phi) = \frac{\int_\Omega I(x).H(\phi)dx}{\int_\Omega H(\phi)dx} \qquad (2)$$

$$c_2(\phi) = \frac{\int_\Omega I(x).(1-H(\phi))dx}{\int_\Omega (1-H(\phi))dx} \qquad (3)$$

By incorporating the length and area energy terms into Eq.(1) and minimizing them, we obtain the corresponding variational level set formulation as follows:

$$\frac{\partial \phi}{\partial t} = \delta(\phi)\left[\mu \nabla\left(\frac{\nabla \phi}{|\nabla \phi|}\right) - \nu - \lambda_1 (I-c_1)^2 + \lambda_2 (I-c_2)^2\right] \qquad (4)$$

where $\mu \geq 0$, $\nu \geq 0$, $\lambda_1 > 0$, $\lambda_2 > 0$ are fixed parameters, μ controls the smoothness of zero level set, ν increases the propagation speed, and λ_1 and λ_2 control the image data driven force inside and outside the contour, respectively. ∇ is the gradient operator. H(Φ) is the Heaviside function and $\delta(\phi)$ is the Dirac function. Generally, the regularized versions are selected as follows:

$$H_\varepsilon(z) = \frac{1}{2}\left(1 + \frac{2}{\pi}\arctan\left(\frac{z}{\varepsilon}\right)\right), \quad z \in R \qquad (5)$$

$$\delta_\varepsilon(z) = \frac{1}{\pi}\frac{\varepsilon}{\varepsilon^2 + z^2}, \quad z \in R \qquad (6)$$

B. LBF model

The SBGFRLS model cannot make full use of the local image information, and the precision of the final evolving contour is not high. The NL-CV model proposed by Bresson et al. is able to overcome this limitation by integrating semi-local and global image information with a specific graph. However how to reasonably define the graph is the key problem. Li et al. proposed the LBF model by embedding the local image information. The model can accurately segment images with intensity in homogeneities with setting the initial contour appropriately. By introducing a kernel function, the LBF model defines an energy functional as follows:

$$E^{LBF} = \lambda_1 \int_\Omega \int_{in(C)} K(x-y)|I(y)-f_1(x)|^2 dydx + \lambda_2 \int_\Omega \int_{out(C)} K(x-y)|I(y)-f_2(x)|^2 dydx \qquad (7)$$

where λ_1 and λ_2 are positive constants, K is a kernel function of a localization property that K(x) decreases and approaches zero with |x| increasing, and f_1 and f_2 are defined as follows:

$$f_1(x) = average(I \in (\{x \in \Omega | \phi(x) < 0\} \cap O_k(x))) \qquad (8)$$
$$f_1(x) = average(I \in (\{x \in \Omega | \phi(x) > 0\} \cap O_k(x))) \qquad (9)$$

where O_k denotes a small neighborhood of the point x. The energy Eq.(7) can be converted to an equivalent level set formulation:

$$E^{LBF} = \lambda_1 \int\left[\int K(x-y)|I(y)-f_2(x)|^2 H(\phi(y))dy\right]dx + \lambda_2 \int\left[\int K(x-y)|I(y)-f_2(x)|^2 (1-H(\phi(y)))dy\right]dx \qquad (10)$$

where H is the Heavside function, can be approximated by Eq.(7). In order to ensure stable evolution of the level set function Φ, a distance regularizing term is added to penalize the deviation of the level set function Φ from the SDF. On the other hand, a length term is used to regularize the zero level curve of Φ. The total variational formulation of the model is as follows:

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$$\frac{\partial\phi}{\partial t} = -\delta_\varepsilon(\phi)\left(\lambda_1\int_\Omega K_\sigma(y-x)\left|I(x)-f_1(y)\right|^2 dy\right) + \delta_\varepsilon(\phi)\lambda_2\int_\Omega K_\sigma(y-x)\left|I(x)-f_2(y)\right|^2 dy + \nu\delta_\varepsilon(\phi)div\left(\frac{\nabla\phi}{|\nabla\phi|}\right)+\mu\left(\Delta\phi - div\left(\frac{\nabla\phi}{|\nabla\phi|}\right)\right) \qquad (11)$$

where f_1 and f_2 can be obtained by

$$f_1(x) = \frac{K_\sigma(x) * \left[H_\varepsilon(\phi)I(x)\right]}{K_\sigma(x) * H_\varepsilon(\phi)} \qquad (12)$$

$$f_1(x) = \frac{K_\sigma(x) * \left[(1-H_\varepsilon(\phi))I(x)\right]}{K_\sigma(x) * (1-H_\varepsilon(\phi))} \qquad (13)$$

and $\delta\varepsilon$ (Φ) can be obtained by the derivative of Eq.(6)

$$\delta_\varepsilon(x) = H'_\varepsilon(x) = \frac{1}{\pi}\frac{\varepsilon}{\varepsilon^2+x^2} \qquad (14)$$

In Eq.(11), the first and the second terms in the right hand side are called the data fitting and the arc length term, respectively, which are responsible for driving the evolving contour towards the object boundaries. The third term called the regularization term serves to maintain the regularity of the level set function. The LBF model utilizes the local region information, and it can obtain aaurate segmentation results, but its computational cost is rather high due to the regularized term and the punished term corresponding to the second term and third term in Eq. (11), respectively. In addition, the model is sensitive to the initial contour.

C. LBF model

In case of image containing a region of interest and background of the same intensity means but with different variances, since the LBF model only exploits local intensity means for segmentation it fails to segment the image correctly. The LGDF model is developed by incorporating more statistical and local intensities into the energy functional. For each pixel x, the local intensities within its neighborhood are assumed to follow a Gaussian distribution

$$p_{i,x}(I(y)\left|u_i(x),\sigma_i(x)^2 = \frac{1}{\sqrt{2\pi}\sigma_i(x)} \exp\left(-\frac{(I(y)-u_i(x))^2}{2\sigma_i(x)^2}\right) \right. \qquad (15)$$

where $u_i(x)$ and $\sigma_i(x)$ are mean and standard deviation of the intensities in each region. The LGDF energy functional is defined as

$$E^{LGDF}(C,u_1,u_2,\sigma_1^2,\sigma_2^2) = -\int_\Omega\int_{insideC} K_\sigma(x-y)\log p_{1,x}(I(y)\left|u_1(x),\sigma_1(x)^2)dydx - \int_\Omega\int_{insideC} K_\sigma(x-y)\log p_{2,x}(I(y)\right|u_2(x),\sigma_2(x)^2)dydx \qquad (16)$$

Here we consider both the first and second order statistics of local intensities, the LGDF model can differentiate regions with similar intensity means but with different intensity variances.

C. LIF model

In this model the local image fitting energy functional is defined by minimizing the difference between the fitted image and the orginal image. The formulation is as follows

$$E^{LIF}(\phi) = \frac{1}{2}\int_\Omega \left|I(x)-I^{LFI}(x)\right|^2 dx, \quad x\in\Omega \qquad (17)$$

where m_1 and m_2 are defined as follows

$$\begin{cases} m_1 = mean(I \in (\{|x\in\Omega|\Phi(x)<0\} \cap W_k(x))) \\ m_2 = mean(I \in (\{|x\in\Omega|\Phi(x)>0\} \cap W_k(x))) \end{cases} \qquad (18)$$

and I^{LFI} the local fitted image formulation is defined as follows

$$I^{LFI} = m_1 H_\varepsilon(\Phi) + m_2(1-H_\varepsilon(\Phi)) \qquad (19)$$

Where φ is the zero level set of a Lipschitz function that represents the contour C, $H_\varepsilon(\Phi)$ is the Heaviside function of the level set φ, and W_k is a truncated Gaussian window with the standard deviation σ and radius k. The LIF model utilizes a filtering method with a Gaussian kernel to regularize the level set function during model optimization. This regularization term not only ensures the smoothness of the level set function, but also enables this model to avoid re-initializing the level set function. As a result, the LIF model is an efficient active contour model that can achieve similar segmentation accuracy to the LBF model with lower computational complexity. Nevertheless, both the LIF and LBF models share the same limitation that they may produce less accurate segmentation results in images with strong noise and intensity in homogeneity.

III. SUMMARY

It should be noted that the CV, LBF and LIF models all use the mean intensity value to characterize either the global or local image information. Because the intensity mean is statistically insufficient to describe a region, these models may fail to segment images with heavy noise and intensity inhomogeneity. To address this issue, other active contour models, such as the LGDF, employ both the first order and second order statistics of local intensities to define the energy functional. Considering the computational efficiency of the LIF model, it is promising to develop a novel active contour model that has simultaneously high segmentation accuracy and low computational cost by incorporating the spatially varying mean and standard deviation of local intensities into the LIF energy functional.

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IV. LOCAL LIKELIHOOD IMAGE FITTING (LLIF) MODEL

An image is represented as a real-valued function $I : \Omega \rightarrow \mathbb{R}$ defined over a rectangular domain $\Omega \subset \mathbb{R}^2$. We assume that the intensity of each pixel x is independently sampled from the probability density function $p(I(x); \theta_i)$, where θ_i is the assembly of distribution parameters. Consider the region of interest in the image domain $\{\Omega_i\}_{i=1}^{M}$ we can define the following parameter space Θ

$$\Theta(x) = \begin{cases} \theta_i & x \in \Omega_i \\ 0 & x \notin \Omega_i \end{cases} \quad with\, i = 1, 2......M \qquad (20)$$

According to the maximum likelihood (ML) criterion, the image segmentation problem can be solved by maximizing the likelihood probability of the observed image w.r.t. the parameters

$$\max_{\Theta} \int_{\Omega} p(I(x); \Theta(x))dx \qquad (21)$$

Applying the negative logarithm to the above equation, maximizing the functional is then converted into the minimizing functional

$$\min_{\Theta} \int_{\Omega} -\log p(I(x); \Theta(x))dx \qquad (22)$$

we assume that the intensity of each pixel follows a local Gaussian distribution to explore the local image information, given by

$$p(I(x); \Theta(x)) = \frac{1}{\sqrt{2\pi S(x)}} \exp\left(-\frac{(I(x)-U(x))^2}{2S(x)}\right) \qquad (23)$$

where U(x) is the mean and S(x) the variance are the spatially varying quantities. Let the neighborhood of pixel x be defined by a Gaussian window W_k with the standard deviation σ and size $(4k + 1) \times (4k + 1)$, where k is the greatest integer smaller than σ. The mean and variance can be calculated using

$$U(x) = \sum_{i=1}^{N} u_i(x) L_i(x) \; and \quad S(x) = \sum_{i=1}^{N} s_i(x) L_i(x) \qquad (24)$$

where $u_i(x)$ and $s_i(x)$ are the mean and variance of the intensities in the region $\Omega_i \cap W_k(x)$ is given by

$$\begin{cases} u_i(x) = mean(I(y) : y \in \Omega_i \cap W_k(x)) \\ s_i(x) = \text{var}(I(y) : y \in \Omega_i \cap W_k(x)) \end{cases} \qquad (25)$$

and $L_i(x)$ is a label indicator of pixel x. If $x \in \Omega_i$, $L_i(x) = 1$; otherwise $L_i(x) = 0$.

In LLIF model spatially varying mean and variance is used. Therefore this model perform very well in segmenting images with heavy noise , particularly in distinguishing regions with similar intensity means but different variances.

A. Level Set Formulation

The image domain Ω consists of two disjoint regions denoted by Ω_1 and Ω_2 . The level set function ϕ is used to represent both Ω_1 and Ω_2 by taking positive and negative sings, given by

$$\begin{cases} \Omega_1 = (x | \phi(x) > 0) \\ \Omega_2 = (x | \phi(x) < 0) \end{cases} \qquad (26)$$

with the Heaviside function H, Ω_1 and Ω_2 can be defined as $M_1(\phi) = H(\phi)$ and $M_2(\phi) = 1 - H(\phi)$. Thus, the energy E^{LLIF} can be expressed as a function of ϕ ,U and S

$$E^{LLIF}(\phi, U, S) = \int_{\Omega} -\log p(I(x) | U(x), S(x))dx \qquad (27)$$

U(x) and S(x) is given by

$$\begin{cases} U(x) = u_1(x)M_1(\phi) + u_2(x)M_2(\phi) \\ S(x) = s_1(x)M_1(\phi) + s_2(x)M_2(\phi) \end{cases} \qquad (28)$$

where

$$\begin{cases} u_1(x) = mean(I(y) : y \in \{\Omega | \phi(y) < 0\} \cap W_k(x)) \\ u_2(x) = mean(I(y) : y \in \{\Omega | \phi(y) > 0\} \cap W_k(x)) \\ s_1(x) = \text{var}(I(y) : y \in \{\Omega | \phi(y) < 0\} \cap W_k(x)) \\ s_2(x) = \text{var}(I(y) : y \in \{\Omega | \phi(y) > 0\} \cap W_k(x)) \end{cases} \qquad (29)$$

The mean U , variance S and the gradient descent flow equation is given by

$$u_i(x) = \frac{\int \omega(y-x) I(y) M_{i,\varepsilon}(\phi(y))dy}{\int \omega(y-x) M_{i,\varepsilon}(\phi(y))dy} \qquad (30)$$

$$s_i(x) = \frac{\int \omega(y-x)(I(y)-U(x))^2 M_{i,\varepsilon}(\phi(y))dy}{\int \omega(y-x) M_{i,\varepsilon}(\phi(y))dy} \qquad (31)$$

In many situations, the level set function will develop shocks, very sharp and/or flat shape during the processing of the evolution, which in turn makes further computation highly inaccurate in numerical approximations To solve this problem, it is necessary to keep the level set function as an approximate signed distance function. The energy functional becomes

$$F(\phi, U, S) = E^{LLIF}(\phi, U, S) + \nu E^{L}(\phi) + \mu E^{P}(\phi) \qquad (32)$$

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where μ and ν are weighting constants and

$$E^P(\phi)=\int\frac{1}{2}\left(\left|\nabla\Phi(x)\right|-1\right)^2 dx$$
$$and \quad E^L(\phi)=\int\left|\nabla H(\Phi(x))\right|dx \qquad (33)$$

Implementing H_ϵ is a smooth function used to approximate the Heaviside function H, δ_ϵ is the derivative of H_ϵ, and ϵ is a positive constant. Thus the energy the energy functional F(ϕ,U,S) can be approximated by

$$F_\varepsilon(\phi,U,S)=E_\varepsilon^{LLIF}(\phi,U,S)+\nu E_\varepsilon{}^L(\phi) + \mu E_\varepsilon{}^P(\phi) \qquad (34)$$

where

$$\begin{cases} H_\varepsilon(x)=\dfrac{1}{2}\left[1+\dfrac{2}{\pi}\arctan\left(\dfrac{x}{\varepsilon}\right)\right] \\ \delta_\varepsilon(x)=\dfrac{1}{\pi}\dfrac{\varepsilon}{\varepsilon^2+x^2} \end{cases} \qquad (35)$$

Minimizing the energy functional F_ϵ w.r.t. ϕ can be achieved by solving the gradient descent flow equation.

$$\frac{\partial\Phi}{\partial t}=-\frac{\partial F_\varepsilon}{\partial\phi}= \delta_\varepsilon(\Phi)\begin{bmatrix}-(s_1-s_2)+2\left(I-U\right)\left(u_1-u_2\right)\\ +\dfrac{\left(I-U\right)^2\left(s_1-s_2\right)}{S}\end{bmatrix} +\nu\delta_\varepsilon(\phi)div\left(\frac{\nabla\Phi}{\left|\nabla\Phi\right|}\right) +\mu\left(\nabla^2\Phi-div\left(\frac{\nabla\Phi}{\left|\nabla\Phi\right|}\right)\right) \qquad (36)$$

B. Implementation

Implementation of our model for the level set formulation can be summarized as follows.

Step 1: Initialize the level set function ϕ.

Step 2: Update local means U and variances S using Eqs. (30) and (31).

Step 3: Update the level set function ϕ according to Eq. (36).

Step 4: Return to Step 2 until the convergence criteria met.

V. RESULTS AND DISCUSSION

This section presents the image segmentation results obtained by applying the proposed LLIF model to CT liver tumor images. In our experiments, the level set function ϕ was simply initialized to a binary step function, which took a negative value $-c_0$ inside the tumor region and a positive value c_0 outside it . Unless otherwise specified, parameters involved in the LLIF model were set as follows: σ = 3.0, time step Δt = 0.05, μ = 2.0, ν = 0.01 x255^2 and e = 2.0.

Fig. 1 demonstrates that the level set approach without re-initialization by Li et al. outperforms the original level set method by Osher and Sethian in tumor detection. Although the approach by Li et al. has achieved a great success, evidence shows that this algorithm requires further improvements. For example, it has been observed that in a noisy image with ambiguous boundaries this approach cannot ideally locate the tumor boundaries (Fig. 2). Fig. 3 illustrates individual performance of using the original level set algorithm and the LLIF model approach, where the former is shown on the first row while the latter is demonstrated on the second row. The original level set method is distracted by the near edges of the liver tumors. LLIF method gets around this problem, and finally addresses on the ideal tumor boundary. This indicates that our approach is able to ignore the interference of neighboring organs edges, and fast approach to the tumor boundary . Segmentation of multiple tumors is shown in Fig. 4. Multiple tumors exist in the image, and different tumors have different intensities. As seen in this figure, the original level set scheme cannot locate the edges of the tumor regions in the liver CT image. The edges have not been correctly outlined. These edges are vague somehow so that the energy minimization in the classical level set function cannot be ideally achieved. The model proposed by Li et al. has a better outcome of tumor detection. The accuracy of the edge detection still needs to be improved.. This may need more efforts to optimize the contour settlement. On the other hand, it is clear that the LLIF model approach has a better performance than these two methods in terms of edge detection (images on the third row). This experiment utilizes a CT liver tumor image where the tumor region is much brighter. The target is to outline the correct tumor region using the available methods. Fig. 5 demonstrates that the LLIF level set scheme has the best performance in tumor detection, where Li's method leads to errors in detecting the exact segmentation of the tumor region . Meanwhile, the original level set method cannot correctly locate the tumor boundary, resulting from the side-effects raised by the image noise. Fig.6 demonstrate how these methods cope with the noisy background. The original level set method failed to segment the tumor region. Meanwhile, Li's model and the LLIF method have been successfully segment the tumor region.. Interestingly, we observe that at iteration 150 fractional order scheme seems reluctant to pick up a concave area. However, it recovers very soon and successfully addresses on the exact tumor region at iteration 350. This may be due to the oscillation of the energy terms during the evolution (before iteration 350). Taking a closer look at the results from Li's model, we observe that this model has less detecting accuracy on the block corners of the tumor region than the LLIF model approach.

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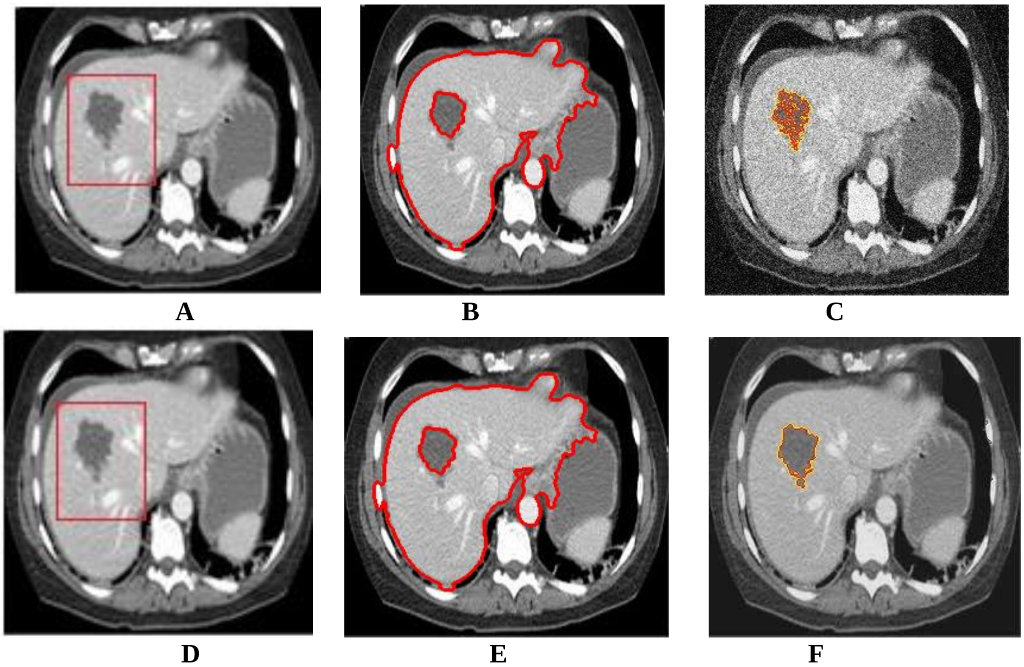

Fig. 1. Performance comparison between the original level set method (first row) and the level set scheme without re-initialization (second row). λ=2.5,μ=0.4,ν=1 and time step = 3. (a) Initial, (b) iteration 200, (c) iteration 350, (d) initial, (e) iteration 200, (f) iteration 300.

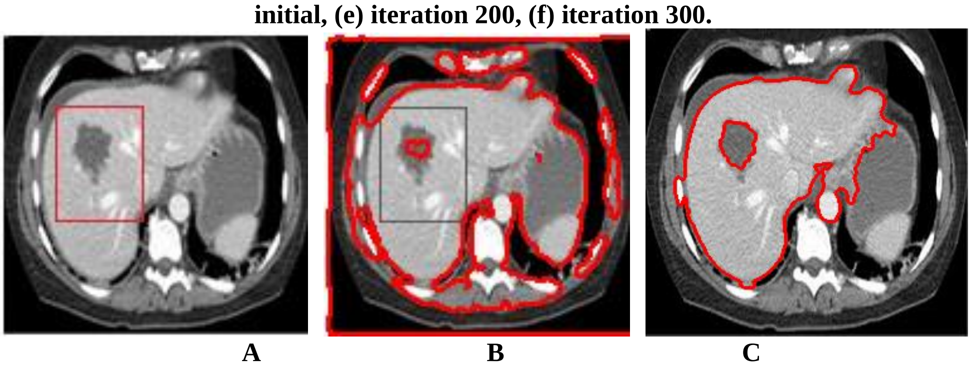

Fig. 2. Performance of the level set scheme without re-initialization. λ= 2.5, μ= 0:4, ν= 1, and time step = 3. (a) Initial, (b) iteration 200, (c) iteration 300.

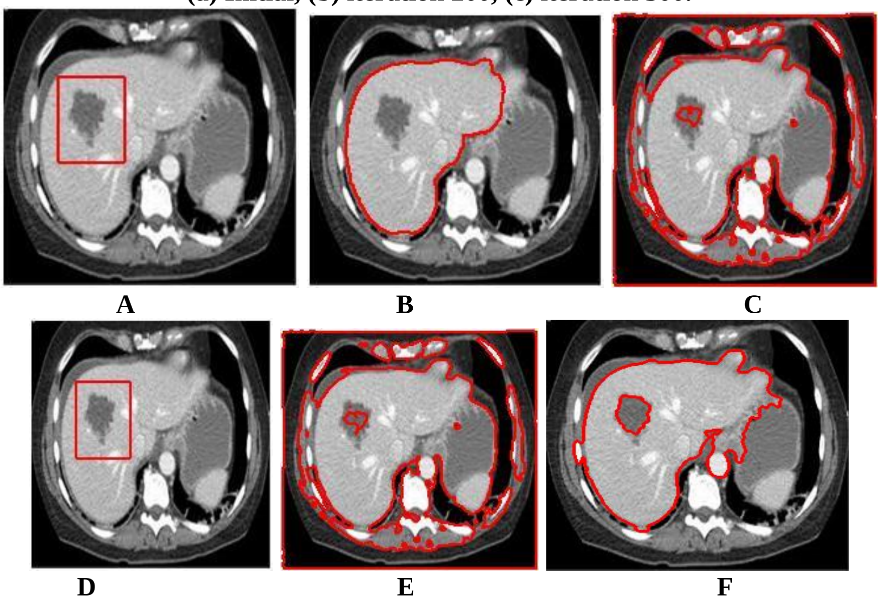

Fig. 3. Performance comparison of the original level set scheme and the LLIF model approach .λ=3,μ=0.3, ν=2, and time step =2.5. (a) Initial, (b) iteration 150, (c) iteration 300, (d) initial, (e) iteration 150, (f) iteration 250.

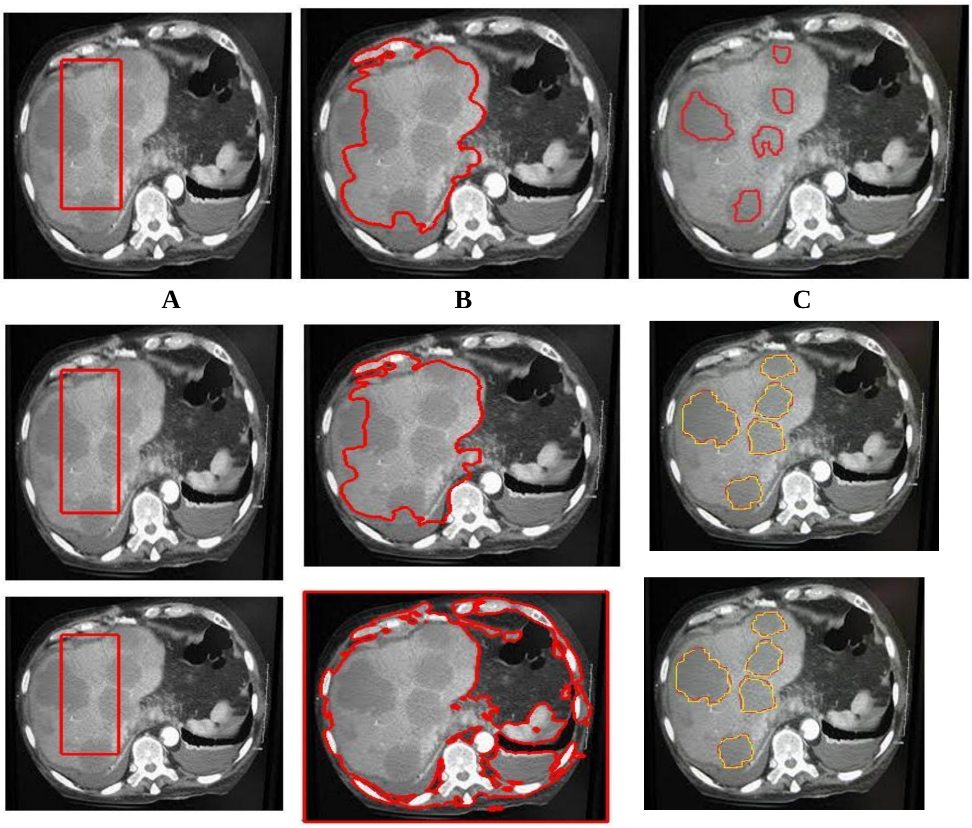

Fig. 4. Performance comparison between the original level set method (first row), the level set scheme without re-initialization (second row), and the LLIF model approach (third row). λ=2.5,μ=0.4, ν=2, and time step=2. 5 (a) Initial, (b) iteration 150, (c) iteration300.

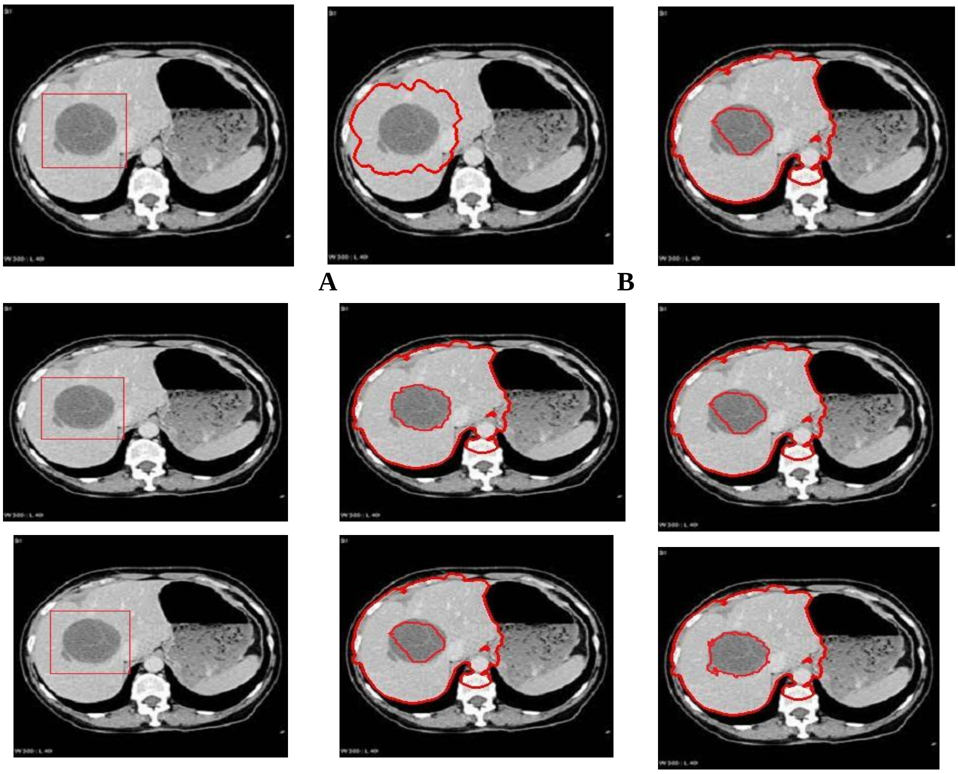

Fig. 5. Performance comparison between the original level set method (first row), the level set scheme without re-initialization (second row), and the LLIF model approach (third row). λ=2.5, μ=0.4, ν=2, and time step =2. 5. (a) Initial, (b) iteration 250, (c) iteration 350.

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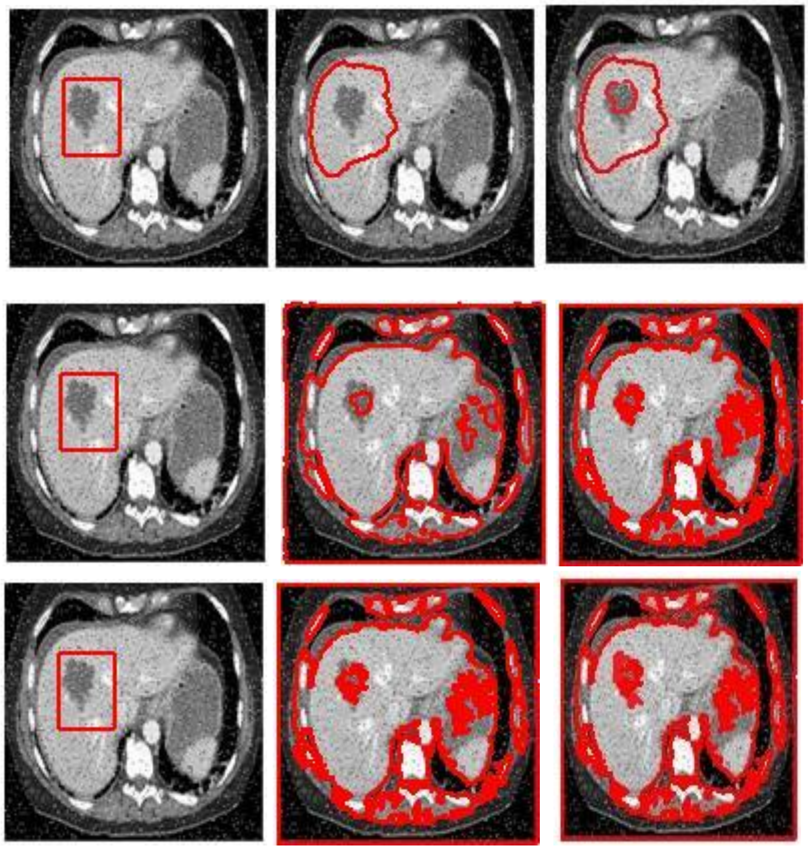

Fig. 6. Performance comparison between the original level set method (first row), the level set scheme without re-initialization (second row), and LLIF model approach (third row). λ=2.5, μ=0.4, ν=2, and time step =2. 5. (a) Initial, (b) iteration 350, (c) iteration 400

VI. CONCLUSION

An effective segmentation tool for liver CT images based on active contour model with local likelihood image fitting term is presented. Level set scheme is used for the analysis. A local likelihood fitting term is included in the energy functional model. By incorporating the local likelihood fitting term, the novel fitting term can describe the original image more accurately, and be robustness to noise. This model is efficient for CT liver images, and intensity inhomogeneous images.

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