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Gallbladder region Extraction from Abdominal CT Image using segmentation tecniques

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Abstract: *This paper proposes traditional level set and region growing methods that request locating initial contour near the final boundary of object have problem of leakage to nearby tissues of gallbladder region. The proposed method consists of a customized fast-marching level set method which generates an optimal initial gallbladder region to solve the problem that the level set method is sensitive to the initial contour location and a modified distance regularized level set method which extracts accurate gallbladder. The novelty in our method is the proper selection and combination of level set methods, furthermore an energy-decrement algorithm and an energy-tune algorithm are proposed to reduce the negative impact of bonding force caused by connected tissue whose intensity is similar with gallbladder. The proposed method is compared to other five state-of-the-art medical image segmentation methods based on a CT image dataset which contains abdominal images from 2 patients. The evaluated results demonstrate that our method outperforms other methods by achieving higher accuracy and making less false segmentation in gallbladder extraction.*
Keywords: *Sigmaid filters, Fast marching level set , Region growing method.*

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I. INTRODUCTION

The two-step seeded region growing (SRG) onto level-set speed images to define an approximate initial liver boundary. The first SRG efficiently divides a CT image into a set of discrete objects based on the gradient information and connectivity. The second SRG detects the objects belonging to the liver based on a 2.5-dimensional shape propagation, which models the segmented liver boundary of the slice immediately above or below the current slice by points being narrow-band, or local maxima of distance from the boundary. With such optimal estimation of the initial liver boundary, our method decreases the computation time by minimizing level-set propagation, which converges at the optimal position within a fixed iteration number. We utilize level-set speed images that have been generally used for level-set propagation to detect the initial liver boundary with the additional help of computationally inexpensive steps, which improves computational efficiency. Finally, a rolling ball algorithm is applied to refine the liver boundary more accurately. Our method was validated on 20 sets of abdominal CT scans and the results were compared with the manually segmented result[1]. The method uses both the object's boundary and region information to achieve robust and accurate segmentation results. The boundary information can help to detect the precise location of the target object and the region information can help to prevent the boundary leakage problem[2]. First a support vector machine (SVM) classifier was trained to extract GB region from one single 2D slice in the intermediate part of a GB by voxel classification. Then the extracted GB contour, after some morphological operations, was projected to the neighboring slices for automated re-sampling, learning and further voxel classification in these slices. This propagation procedure continued till all GB-containing slices were processed The method was tested using 18 CT data sets and a set of quantitative measures were computed[3]. Level set methods have been widely used in image processing and computer vision. In conventional level set formulations, the level set function typically develops irregularities during its evolution, which may cause numerical errors and eventually destroy the stability of the evolution. Therefore, a numerical remedy, called reinitialization, is typically applied to periodically replace the degraded level set function with a signed distance function. a new variational level set formulation in which the regularity of the level set function is intrinsically maintained during the level set evolution. The level set evolution is derived as the gradient flow that minimizes an energy functional with a distance regularization term and an external energy that drives the motion of the zero level set toward desired locations. DRLSE also allows the use of more general and efficient initialization of the level set function. In its numerical implementation, relatively large time steps can be used in the finite difference scheme to reduce the number of iterations, while ensuring sufficient numerical accuracy[4]. Manual segmentation was used as a last resort. Then strong filtering and fidence connected region growing algorithm were applied to rebuild from each healthy and pathological liver a multi compartment model including parenchyma, arteries and veins. The precision of the obtained vasculator model allowed anatomical classification of hepatic segments and the quantifictation of their volumes.[5]

II. MATERIALS AND METHODS

The novel hybrid gallbladder segmentation method combines a first-marching level set method and a modified distance regularized level set (MDRLS) method. The MDRLS method exploits a distant regularized level set evolution (DRLSE) scheme proposed in [2]. Since MDRLS eliminates the need of reinitialization of level set function via inherently maintaining a signed distance profile near the zero level set, it is able to provide accurate numerical calculation in level set evolution. Moreover, an energy-tune function employed in MDRLS can weaken the bonding force which appears in weak boundary area. Therefore, the MDRLS can overcome the shortage of oversegmentation in weak boundary region and can keep a stable evolution even in complex texture surroundings of the gallbladder. However, MDRLS needs amount of computation, and level set evolution is sensitive to initial position of the zero level set contour. A nonideal initial position reduces the accuracy of segmentation and increases the calculation time. In order to solve these problems, a customized fast-marching level set method based on multiple seeds is used to provide an optimal initial gallbladder region for the MDRLS method and improves the efficiency of computing. The initial gallbladder region is generated based on gradient features of gallbladder, so it is adapted for gallbladder texture structure. Moreover it covers different parts of gallbladder region due to multiple seeds. Besides, an energy-decrement algorithm is applied to preserve the initial gallbladder region from leaking into nearby tissues. The initial gallbladder region generated by fastmarching method is optimal and meets the requirement of initial contour position of zero level set. Therefore, the proposed hybrid level set method is time effective and able to achieve accurate segmentation results in gallbladder extraction from CT images.The collaboration of the two level methods and the energy-tune algorithm is described as follows (Figure 1).

(1) First an anisotropic diffusion filter is used to denoise the input CT image.
(2) A gradient magnitude filter generates the gradient map of the denoised CT image.
(3) A sigmoid filter forms an edge feature image based on the gradient map.
(4) The energy-decrement filter optimizes the edge feature image to form an edge energy map based on standard lines.
(5) Then the edge energy map is applied to modify fastmarching level set which generates an optimal initial gallbladder region.
(6) An energy-tune filter applies an energy-tune algorithm to adjust the gradient map of CT image to generate an energy feature map.
(7) The energy feature map is used to modify distance regularized level set method.Then the actual gallbladder is extracted using modified distance regularized level set method based on initial gallbladder region.
(8) Finally the actual gallbladder is thresholded and smoothed. The details of the aforementioned processing are described in the remaining content of this section

2.1. Denoising of CT Image. Since the intensity distribution of the gallbladder is irregular due to the noise caused in the image formation stage, the abdominal CT images are necessarily denoised in preprocess. Moreover, boundaries of gallbladder region which connect to neighboring organs are usually fuzzy. The important edges are easily blurred and detail of organs is significantly lost after the CT image is smoothed using a simple Gaussian filter. Therefore, a modified curvature diffusion equation (MCDE) [6] based anisotropic diffusion filter [7] is employed to reduce the influence of noise while preserving the boundaries and details of organs.

2.2. Energy-Decrement and Energy-Tune Algorithm. Seg-mentation results of fast-marching are significantly impacted by the contour propagation speed map and are easy to leak into nearby tissues in a weak boundary. A simple energy-decrement algorithm is proposed to prevent initial gallbladder region generated by fast-marching level method beyond the authentic gallbladder region. A precondition of the algorithm is that a standard line is drawn by the physician. The standard line is used to define the coupling area and separates two organs . The energy-decrement function is defined by

$$e_s(i,j) = \begin{cases} J_{min} \; D_l < T_d \\ J,(i,j) \; otherwise \end{cases} \qquad (1)$$

where Imin is the minimum value of contour propagation speed map. $Dl(i, j)$ is the shortest distance of pixel (i, j) to standard line. Td is a distance threshold. If a distance of pixel to standard line is less than Td, that means it is closed to standard line, its energy is set as the minimum value of contour propagation speed map. Energy map Es is used as feature map instead of contour propagation speed map in fast-marching level set method. An energy-tune scheme is employed to support the level set function (LSF) evolution in modified distance regularized level set (MDRLS) method. An edge indicator function g is defined to obtain edge feature map as follows:

$$g \triangleq \frac{1}{1+g_m^2}, \qquad (2)$$

where gm is gradient magnitude of the CT image which has been preprocessed. This function g normally takes smaller value at boundaries of object than at any other location. It resists noise. Its values belong to [0, 1]. Since edges located in connected regions between gallbladder and its adjacent organs are weak, even fractured, the edge indicator is likely to set a large value at weak boundaries. This leads to oversegmentation in level set evolution. Gallbladder and other organs have high energy after processing by edge indicator. It is assumed that the boundary regions which have high energy are caused by energy leaking of organs. An energy-tune algorithm is proposed to decay leaked energy in boundary regions. It restrains oversegmentation caused by bonding force. It is considered that the closer a pixel is to the energy source, the more energy it obtains. The initial gallbladder region generated using fast-marching is considered as energy source. Besides, the standard line is also applied to label the intensity similar area between two organs. The energy of each pixel that comes from energy source is defined as

$$e(i,j) = \sum_{(i_o,j_0)\in R_0} e^{-(D(P_{i,j},P_{i,j})/\sigma}\, g(i_0,j_0) \qquad (3)$$

where $E(i,\ j)$ is energy of pixel $(i,\ j)$. $R0$ is energy source. $D(pi,j,\ pi0,j0\ )$ is Euclidean distance between pixel $(i0,\ j0)$ of energy source and pixel$(i,\ j)$. g is edge feature map.The closer a pixel is to energy source, the larger energy it absorbs from the energy source. The energy-tune function is defined by

$$e_t(i,j) = \begin{cases} \min\,(1, \frac{1}{n}\alpha e(i,j) + g(i,j) & if\,(i,j) \in R_0 \\ \max\left(0, g(i,j) - \frac{\beta e(i,j)}{D_l(i,j)}\right) & if D_l \le D_r \\ g(i,j) & otherwise \end{cases} \qquad (4)$$

where $e_t(i,\ j)$ is adjusted energy of pixel $(i,\ j)$. $R0$ is energy source. n is total number of pixels in energy source. Dl is shortest distance of pixel $(i,\ j)$ to standard line. Similarly Dr is shortest distance of pixel $(i,\ j)$ to energy source. g is edge feature map. α and β are parameters to control energy tune. The energy-tune function decays the energy of pixels closed to standard line but far from energy source, but enhances the energy of pixels that belong to the initial gallbladder region. Moreover, we also propose an automatic energy-tune algorithm, which does not depend on standard line. The initial gallbladder region is still regarded as energy source. A distance threshold Dt is defined to partition the energy tune area. If the shortest distance of a pixel to energy source is farther than threshold, its energy will be significantly decayed.

2.3. Initial Gallbladder Region Extraction.

An optimal initial gallbladder region in the denoised CT image is generated using a fast-marching level set method based on multiple seed points. The fast-marching level set method consists of five steps:

(1) calculation of intensity gradient magnitude,

(2) calculation of contour propagation speed map based on gradient magnitude,

(3) calculation of energy map using energy-decrement algorithm based on contour propagation map,

(4) calculation of time-crossing map which indicates, for each pixel, how much time it would take for the front to arrive at the pixel location,

(5) generation of the optimal initial gallbladder region based on time-crossing map. First, magnitude of the image gradient at each pixel location is computed.

The image is smoothed by convolving it with a Gaussian kernel and then applied a differential operator to generate gradient magnitude. An infinite impulse response filter [1] that approximates a convolution with the derivative of the Gaussian kernel is employed in the computational process. Second, a sigmoid filter [8] is applied to calculate the active contour propagation speed map based on the gradient magnitude. Sigmoid intensity transformation is represented by the following equation:

$$I(x,y) = (Max - Min)\frac{1}{1-e^{-(^{(g_m(x,y)-\beta)}/_{\alpha})}} + Min$$

(6)

where Min and Max are the minimum and maximum values of the output value of sigmoid filter. $gm(x, y)$ is gradient magnitude at pixel (x, y). α defines the width of the gradient magnitude range, and β defines the gradient magnitude around which the range is centered; they are used to control exaggerating of intensity differences between gallbladder and other organs. Min is always set to 0 and Max is set to 1. Third, the contour propagation map is processing using energy-decrement algorithm to form energy map (Figure 3(f)). Then time-crossing map which indicates the arrival time of the active contour propagation at each pixel was calculated using a fast scheme. Let $T(x, y)$ be the time at which the curve crosses the point (x, y). The surface $T(x, y)$satisfies the following equation:

$$|\nabla T|\ Et = 1, \qquad (7)$$

where Et is energy map. If standard line is not defined, Et is replaced by contour propagation speed map I. Finally, an optimal initial gallbladder region is extracted by defining a time threshold to take a snapshot of the contour at a particular time during its evolution from the time-crossing map.

2.4. Modified Distance Regularized Level Set Method.

The actual gallbladder region is extracted using a modified distance regularized level set method based on the initial gallbladder region. where p is a double-well potential function for the distance regularization term Rp and is constructed a

$$p(s) = \begin{cases} \frac{1}{2\pi^2}(1-\cos(2\pi s)), if \;\; s \le 0 \\ \frac{1}{2}(s-1)^2, \qquad\qquad if \;\; s > 1 \end{cases}$$

(10)

In order to decrease leakages to nearby tissues in segmentation results, a modified distance regularization level set method, based on the energy-tune algorithm, is proposed. The energy-tune algorithm is used to modify the original distance regularization level set method. The energy function $E(\phi)$for the modified level set functionΦ:Ω→R is defined by

$$E(\emptyset) = \mu R_p(\emptyset) + \lambda\, d\theta \int_\Omega E_t \delta_\varepsilon(\phi)|\nabla\phi|\, dx + \alpha \int_\Omega E_t H_\varepsilon(-\phi)\, dx$$

(11)

The third energy term represents area force which is necessarily employed to speed up the propagation motion of zero level set when the initial contour is far away from the desired object boundaries. The propagation speed of the zero level set contour would slow down when it closes to object boundaries, since energy map Et takes small value at the boundaries. The initial gallbladder region is used to construct initial level set function (LSF) $\phi 0$ as a binary step function. Consider

$$\phi_0(x) = \begin{cases} -c, & if\ x\epsilon R_0 \\ c, & otherwise \end{cases}$$

(13)

where c>0 is a constant and $R0$ is the initial gallbladder region. c is always positive in gallbladder segmentation. The level set evolution equation in MDRLS formulation is finally defined by

$$\frac{\partial\phi}{\partial t} = \mu div(|\nabla_\phi|\nabla_\phi) + \lambda\delta_\varepsilon(\phi) div(E_t \frac{\nabla\phi}{|\nabla\phi|}$$

(14)

where div (·) is the divergence operator and dp is a function defined in [4]

$$d_p(s) \triangleq \frac{P'(s)}{s}$$

(15)

The distance regularization term is able to intrinsically maintain a signed distance profile near the zero level set and eliminates the need for reinitialization of level set function. Therefore, induced numerical errors caused by reinitialization are avoided. Besides, edge-based active contour model is an advantage in optimal segmentation of local object. Thus, the edge-based active contour model in MDRLS formulation is more suitable for gallbladder segmentation under the complicated surrounding due to stable and accurate numerical computation. 2.5. Actual Gallbladder Region Extraction. In practical gallbladder region extraction process, a two-phase-segmentation scheme is employed based on the edge-based MDRLS level set method. The first phase can be seen as a high speed level set evolution, and the second phase can be seen as a high accurate zero level set contour evolution. Two iteration numbers, an interiteration number and an outeriteration number, are, respectively, applied in different phases. In the first phase, the zero level set is initialized as a binary step function in accordance with the function (3). Since intensity distribution of gallbladder region is irregular and boundary is usually not well defined, a small coefficient α is set to -1 for the energy term $\int \Omega\ EtH\varepsilon(-\phi)dx$ in order to prevent contour from expanding too rapidly and preserve the zero level set contour from crossing the boundary of gallbladder region. λ is usually set larger than μ. A relatively large weight is assigned to energy term $\int \Omega\ Et\delta\varepsilon(\phi)|\nabla\phi|dx$ that means a stronger constraint force of boundary pushes zero level set curve towards boundary while limiting the oversegmentation of gallbladder region. The interiteration is used to define the level set evolution time in first phase. After first phase evolution, the zero level set contour is closed to the object boundary. In the second phase, the main purpose is to accurately extract the gallbladder region. The level set evolution equation is reset as

$$\frac{\partial\phi}{\partial t} = \mu div(d_p(|\nabla\phi|\nabla\phi) + \lambda\delta_\varepsilon(\phi)div(E_t\frac{\nabla\phi}{|\nabla\phi|} \quad (16)$$

The energy term $\int \Omega\ EtH\varepsilon(-\phi)dx$ which is used to speed up the motion of zero level set contour is abolished by setting α=0, since a high speed expanding is likely to make the contour across the object boundary and then causes oversegmentation. Level set evolution is dominated by edge force in second phase. The outeriteration is used to define evolution time. The actual gallbladder region is finally optimized by using open operation and closing operation to smooth the boundary of gallbladder while keeping the original shape. The small holes inside the gallbladder region are filled, and the tiny noise is eliminated.

III. CONCLUSION

The proposed hybrid level set method effectively incorporates a fast-marching level set method and a modified distance regularized level set method to extract gallbladder from CT image. Our main contribution is coming up with a feasible segmentation scheme and achieving better accuracy and time efficiency in gallbladder extraction. Our hybrid level set method needs fewer and simple human-computer interaction. Based on energy-tune algorithm, the hybrid level set method overcomes the shortages of segmentation of object with nonideal edges in the complex texture of medical images. The modified distance regularized level set evolution provides stable and accurate numerical computation. Moreover, a two-phase-segmentation scheme is employed in MDRLS for further preventing the oversegmentation in gallbladder region of nonideal edges. A fast-marching level set method employed in our method is able to generate optimal initial region for MDRLS in a short time while effectively improving segmentation speed. Therefore, the proposed hybrid level set method not only achieves accurate segmentation results but also is simultaneously time efficient. In the future, we would apply the proposed hybrid level set method to extract other organs, such as liver, spleen, and heart. Moreover, we would utilize a priori knowledge including shape, location, and intensity distribution to guide the gallbladder ssegmentation. A full-automatic algorithm is our next research target.

IV. FUTURE WORK

In the future, we would apply the proposed hybrid level set method to extract other organs, such as liver, spleen, and heart. Moreover, we would utilize a priori knowledge including shape, location, and intensity distribution to guide the pancreas segmentation. A full-automatic algorithm is our next research target

REFERENCE

[1]. Jeongjin Lee a, Namkug Kimb, Ho Lee a, Joon Beom Seo b, Hyung Jin Wonb, Yong Moon Shinb,∗, Yeong Gil Shina, Soo-Hong Kimc, " Efficient liver segmentation using a level-set method with optimal detection of the initial liver boundary from level-set speed images", computer methods and programs in biomedicine vol. 88 pp. 26–38, July 2007.

[2]. Yan Zhang1, Bogdan J. Matuszewski1, Lik-Kwan Shark 1, Christopher J. Moore2, "Medical Image Segmentation Using New Hybrid Level-Set Method" Fifth International Conference BioMedical Visualization, July 2008.

[3]. Jiayin Zhou , Weimin Huang , Jing Zhang, " Segmentation of Gallbladder from CT Images for A Surgical Training System" International Conference on Biomedical Engineering and Informatics,no3,vol4,2010.

[4]. Chunming Li, Chenyang Xu, "Distance Regularized Level Set Evolution and Its Application to Image Segmentation" ieee transactions on image processing, vol. 19, no. 12, december 2010

[5]. Anik Barthod-Malat, Veronika kopylova, Gennady I. Podoprigora, Taroslav R. Nartsissov, Orland angoue, Philippe G. Young, Jean-Marie Crolet, and Oleg Blagosklonov "Development of Multi-comapartment Model of the liver using iamge-based Meshing software" 34th Annual International Conference of the IEEE EMBS San Diego, California USA, 28 August - 1 September, 2012.

[6]. R. T. Whitaker and X. Xue, "Variable-conductance, level-set curvature for image denoising," in Proceedings of the IEEE International Conference on Image Processing (ICIP '10), vol. 1, pp. 142–145, October 2001.

[7]. P. Perona and J. Malik, "Scale-space and edge detection using anisotropic diffusion," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 12, no. 7, pp. 629–639, 1990.

[8]. R. Deriche, "Recursively implementing the gaussian and its derivatives," Tech. Rep. 1893, Unite de recherche INRIA SophiaAntipolis, 1993.

[9]. J. A. Sethian, "Fast marching methods," SIAM Review, vol. 41, no. 2, pp. 199–235, 1999

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