

## Locating Liver Lesion with Local C-V Level Set and Image Registration

Zhaohui Luo\*, Xi Zaifang, Wang Junnian

School of Information and Electrical Engineering, Hunan University of Science and Technology  
Xiangtan, China

\*Corresponding author, e-mail: Luozaohui01@sina.com

### Abstract

*In this paper, we proposed comprehensive methods to locate the liver lesion in multi-phase CT images. It first construct a local liver lesion image from the image in which liver lesion differs from liver tissue most markedly, then pre-segment the lesion with OTSU method to get the initial contour, and evolve the active contour with local C-V level set method to get the final contour of lesion in the CT image. Finally locate the liver lesion in CT images of other phases by image registration. Experiments showed this method can extract liver tumor efficiently. A well-prepared abstract enables the reader to identify the basic content of a document quickly and accurately, to determine its relevance to their interests, and thus to decide whether to read the document in its entirety.*

**Keywords:** local level set, OTSU method, image register

**Copyright © 2014 Institute of Advanced Engineering and Science. All rights reserved.**

### 1. Introduction

Hepatocellular carcinoma (HCC) is one of the most common malignancies in the world, with approximately 1,000,000 cases reported every year. X-ray computed tomography (CT) is one of sensitive imaging modalities for the liver tumor analysis [1]. Spiral CT, with the recent introduction of multi detector- row scan technology (MDCT), currently plays a fundamental role in the diagnosis and staging of HCC.

Multi-phase helical CT is the most suitable technique. It usually includes the plain CT images and enhanced CT images, which can increase the detection and improve the characterization of focal liver lesions by using contrast agents.

a quadruple-phase protocol that includes unenhanced, hepatic arterial, portal venous, and delayed phase images. It provides dynamic information of the blood supply of liver lesions. The different blood supply to the lesion, in fact, is the most important CT feature that may help differentiate among small hepatocellular lesions that have emerged in a cirrhotic liver the multiphase examination [2-4].

However, it also costs them more burdens because of the increasing amount of data they need to interpret [1]. Recently, computer-aided diagnosis (CAD), defined as a diagnosis introduced by a radiologist who uses the output from a computerized analysis of medical images in detecting lesions, assessing extent of disease, and making diagnostic decisions is being used to reduce the burdens [5].

In a liver cancer CAD system, the first step is to locate the liver lesions, i.e. extract the region of interest (ROI) for further analysis. A successful CAD system depends on the correct segmentation of liver lesions. In abdominal CT images, there are many organs such as heart, stomach, and spleen besides liver, which make the images more complicated. On the other hand, each patient is unique, so the shape and feature of the liver is diversified. What's more, most of liver lesions diverse in different phase CT images [3]. These account for the hardness of segment the liver lesion and the interests of many researchers.

There are many approaches for segmentation in medical images, such as threshold, contour based techniques, region based techniques, clustering, and template matching. Each of these approaches has its advantages and disadvantages in terms of applicability, suitability, performance, and computational cost [5, 6]. Active contours have been extensively studied and widely used in medical image segmentation, particularly to locate boundaries, where an initial

contour is deformed towards the boundary of the object to detected by the minimizing energy function. But the parametric deformable models have difficulties with segmentation of topologically complex structures. To overcome these problem, the level set approach was introduced by S.Osher and J.A.Sethian [7]. They model the propagating curve as a specific level set of a higher dimensional surface [8].

By studying the abdominal CT images, we find that although the images are complicated, inside the region of liver, the images are relatively simple. In one of the quadruple-phase CT images, the lesion has different CT value from normal liver tissue and can be distinguished by eyesight. In this paper, we propose a local level set algorithm combining image register method to locate liver lesion. The steps of are as follows:

- a) Select the CT image in which the lesion's dense differs most greatly from the liver tissue and can be distinguished by eyesight in the quadruple-phase CT images as the reference image for the segmentation of liver lesion;
- b) In the reference image choose several points inside the liver area manually and form a polygon which covers the whole lesion to construct a local lesion image;
- c) Pre-segment the lesion with multilevel OTSU methods to form the initial contour;
- d) Evolve the active contour with multiphase C-V level set methods to get the final contour of lesion;
- e) Use the image register methods and map the area of lesion into other phase CT image.

The remainder of this paper is structured as follows. In Section 2, C-V level set [7] is introduced briefly, in section 3, we describes the local C-V level set algorithm combining OTSU method. Section 4 details the experimental procedure of segmentation, data set. Results are also examined and discussed.

In section 5 we describe the image registration methods and detail the corresponding experiment procedure in section 6.

The conclusion is drawn in Section 7. Finally, possibilities for future work are outlined.

## 2. The Description of C-V Method

The C-V method [10], integrating the level set and Mumford-Shah model, does not use the gradient information. It minimizes the energy function approach to evolution the curve. The

image  $u(x,y)$  is formed by two regions: object ( $u_i$ ) and background ( $u_o$ ), which is separated by the evolving curve  $C$  in  $\Omega$ . The constants,  $c_1$  and  $c_2$  depending on  $C$ , are the averages of image  $I$  inside  $C$  and respectively outside  $C$ . Chan and Vese introduce the energy functional  $E(c_1, c_2, C)$  defined by:

$$E(c_1, c_2, C) = \mu \text{Length}(C) + \nu \text{Area}(u_i) + l_1 \int_{u_i} |u(x,y) - c_1|^2 dx dy + l_2 \int_{u_o} |u(x,y) - c_2|^2 dx dy \quad (1)$$

Here  $\text{Length}(C)$  is the length of the curve  $C$ , and  $\text{Area}(u_i)$  is the area of the region inside  $C$ ,  $\mu, \nu \geq 0$ ,  $l_1, l_2 > 0$  are fixed parameters. Therefore the energy function is minimized if the curve is on the boundary of the object. Optimization (1), it can get the ultimate segmentation line  $C$ , as well as the location of the unknown  $c_1, c_2$ .

Using the Heaviside function  $H(z)$ , and the one dimensional Dirac measure  $\delta(z)$ , and defined, respectively, by:

$$H(z) = \begin{cases} 1, & \text{if } z \geq 0 \\ 0, & \text{if } z < 0 \end{cases}, \quad d(z) = \frac{d}{dz} H(z) \quad (2)$$

Partial differential equations, gotten by Chan and Vese using Euler-Lagrange method, are as follows:

$$\begin{aligned} \frac{\partial f}{\partial t} &= d(f) \operatorname{div} \left( \frac{\tilde{\nabla} f}{|\tilde{\nabla} f|} \right) - u - l_1(u - c_1)^2 + l_2(u - c_2)^2 = 0 \\ f(x, y, 0) &= f_0(x, y) \\ \frac{d(f)}{|\tilde{\nabla} f|} \times \frac{\partial f}{\partial n} &= 0 \end{aligned} \tag{3}$$

Where the  $c_1, c_2$  can get from the following equations.

$$c_1(f) = \frac{\int_{\Omega} u(x, y) H(f(x, y)) dx dy}{\int_{\Omega} H(f(x, y)) dx dy} \tag{4}$$

$$c_2(f) = \frac{\int_{\Omega} u(x, y) (1 - H(f(x, y))) dx dy}{\int_{\Omega} (1 - H(f(x, y))) dx dy} \tag{5}$$

In the numerical calculations, the regularizing function (6) is used to replace  $H(z), \delta(z)$  respectively.

$$\begin{aligned} H_{\varepsilon}(z) &= \frac{1}{2} \left[ 1 + \frac{2}{\pi} \arctan\left(\frac{z}{\varepsilon}\right) \right], \\ \delta_{\varepsilon}(z) &= \frac{1}{\pi} \cdot \frac{\varepsilon}{\varepsilon^2 + z^2} \end{aligned} \tag{6}$$

So that the gradient flow Equation (3) roles in all of the level set, and we can automatically monitor the empty goal with the internal region, and make the overall energy function to the minimum.

Let's disperse the equation in  $f$ , use a finite differences implicit scheme. Recall first the usual notations: let  $h$  be the space step,  $\Delta t$  be the time step, and  $(x_i, y_j) = (ih, jh)$ , be the grid points. Here

$1 \leq i, j \leq M$ , . The approximation of  $\phi(t, x, y)$  are set by  $\phi_{i,j}^n = \phi(n \Delta t, x_i, y_j)$ . From (3), we can get  $\phi^n$ . The  $c_1(\phi^n), c_2(\phi^n)$  can be got respectively by (4), (5). Chan and Vese calculate  $\phi^{n+1}$  through (7).

$$\begin{aligned} \frac{f_{i,j}^{n+1} - f_{i,j}^n}{\Delta t} &= \frac{m}{h} D_x \frac{f_{i+1,j}^n - f_{i,j}^n}{\sqrt{(f_{i+1,j}^n - f_{i,j}^n)^2 + (f_{i,j+1}^n - f_{i,j}^n)^2}} \\ &+ \frac{m}{h} D_y \frac{f_{i,j+1}^n - f_{i,j}^n}{\sqrt{(f_{i+1,j}^n - f_{i,j}^n)^2 + (f_{i,j+1}^n - f_{i,j}^n)^2}} - v - l_1(u_{1i,j} - C_{1i,j})^2 - l_2(u_{2i,j} - C_{2j,j})^2 \psi(f_{i,j}^n) \end{aligned} \tag{7}$$

From the Equation (3), we can see, the definition of partial differential equations involving image function  $I(x, y)$  is domain-wide map data, and the definition of other two unknown  $c_1, c_2$  is also image definition of the region, with the overall characteristics. Hence, updating level set function is in the entire defined region, the computation is very large [11].

### 3. Local C-V Level Set for the Segmentation of Liver Lesions

The C-V model can only partition an image into two regions, i.e. object and background. While in an abdominal CT images, there are many organs such as heart, stomach, and spleen besides liver, which make the images more complicated and consist of more than two regions, so the C-V level set can not be applied for the segment of liver lesions directly.

As we can see, the liver region is relatively simple compared with the whole abdominal CT image, and in the local area, the lesion can be easily distinguished from normal liver tissue, so we focus our attention on the local area. We select several points to form a polygon which covers the whole lesion and construct a local lesion image of the smallest size. Then the evolution of the contour is processed only in the local images. This method can get rid of the interference of other organs. In addition, because the size of the local image is much fewer than that of the whole abdominal CT image, the evolution of contour can be speeded up.

As in (4), (5),  $c_1$  and  $c_2$  depending on  $C$ , are the averages of image  $I$  inside  $C$  and outside  $C$  respectively. A local image includes the marginal region outside the polygon besides lesion and liver organ. To apply the C-V level set to the segmentation of liver lesion, we redefine  $c_2$  as the average gray level of liver region, as shown in (8).

$$c_2(f) = \frac{\int_{\Omega} u(x,y) [1 - H(f(x,y))] H_{mask}(x,y) dx dy}{\int_{\Omega} [1 - H(f(x,y))] H_{mask}(x,y) dx dy} \quad (1)$$

Because of the local character of this method, the initialization of the level set functions plays an important role in segmentation of an image. If the initial contour is close to the boundary of lesion, the iteration of evolution can be lessened. We apply the multilevel OTSU method proposed by Otsu to pre-segment the local image to get ideal initial contour.

In the OTSU method, only the gray-level histogram suffices without other a priori knowledge, and the feasibility of evaluating the "goodness" of threshold is done through exhaustive search to minimize the within-class variance between dark and bright regions of the image. Although many works on threshold methods have been proposed in a number of literatures, the OTSU method [9], which is a method that minimizes the within-class variance, is a popular non-parametric method for its simplicity and efficiency.

In Otsu's method we exhaustively search for the threshold that minimizes the intra-class variance (the variance within the class), defined as a weighted sum of variances of the two classes:

$$T_h = \arg \min \{ w_0(t) s_1^2(t) + w_1(t) s_2^2(t) \} \quad (9)$$

Here  $w_i$  are the probabilities of the two classes separated by a threshold  $T_h$  and  $s_i^2(t)$  are variances of these classes.

Otsu shows that minimizing the intra-class variance is the same as maximizing inter-class variance.

To get rid of the interference of the marginal area of the local image, we only calculate the region inside the polygon. The optimal threshold  $T_h$  can be obtained by minimizing the within-class variance in (9). We then pre-segment the local image inside the polygon, and partition it into two regions, i.e. lesion and liver tissue. The gray level of the marginal area is zero, and may be mistaken for lesion. To eliminate the impact, we fill the marginal area with the average gray level of liver tissue. When the gray level of liver lesion is higher than liver tissue, the initial level set function  $\phi$  is constructed by (10), otherwise, it is constructed by (11).

$$f(x,y,0) = u(x,y) - T_h \quad (10)$$

$$f(x,y,0) = T_h - u(x,y) \quad (11)$$

Then the level set function  $\phi$  is updated according to (7). After several iterations, we get the final contour and extract the lesion. By mending C-V level set, we can get rid of the impact

of other organs. In addition, because the size of the local image is much fewer than that of the whole abdominal CT image, the evolution of contour can be speeded up greatly. We call the mended method local level set.

#### 4. Experiments of Segmentation

We tested the proposed method on two images. The first one is shown in Figure 1(a). There is a tumor of high density, i.e higher gray level in the bottom of the liver. We select four points and construct a polygon to besiege the tumor, as shown in Figure 1(a). The local image is shown in Figure 2(a). By using OTSU method pre-segment the image first, as shown in Figure 2(b). To decrease the gradient of the boundary of the polygon, we filled the empty area outside the polygon with the mean CT value of the liver, as shown in Figure 2(c). We can see that the initial contour shown in Figure 2(d) is near the boundary of the lesion, but there are some dissociative areas inside or outside the tumor. Then the contour was evolved with the

local level set method. The parameters are as follows: time-step  $Dt = 0.3$ ,  $m = 850$ ,  $l_1 = l_2 = 1$ . After 50 iterations, we got the final contour, as shown in Figure 2(e). The distribution of level set is shown in Figure 3 and the final contour in the source image is shown in Figure 4, we can see that the contour is just on the boundary of the lesion.

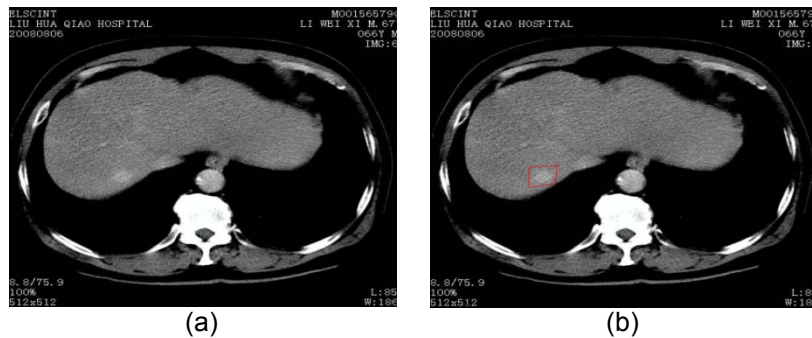


Figure 1. High Density Lesion

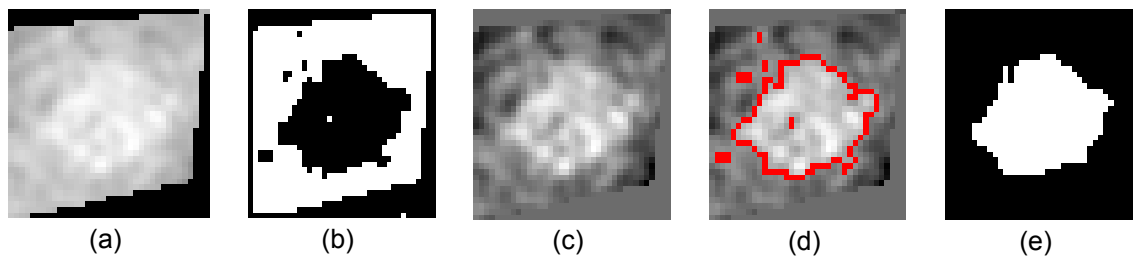


Figure 2 .The Process and Result of the First Experiment

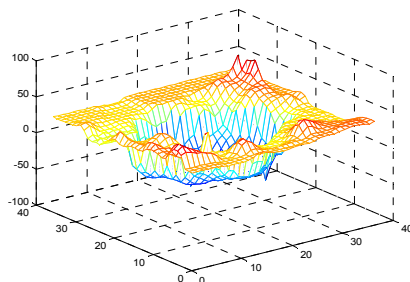


Figure 3. The Distribution of Level Set of the First Experiment

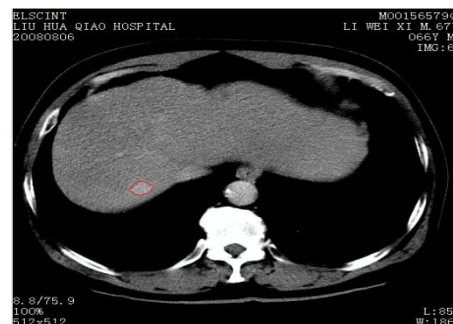


Figure 4.The Final Contour Line of High Density Lesion

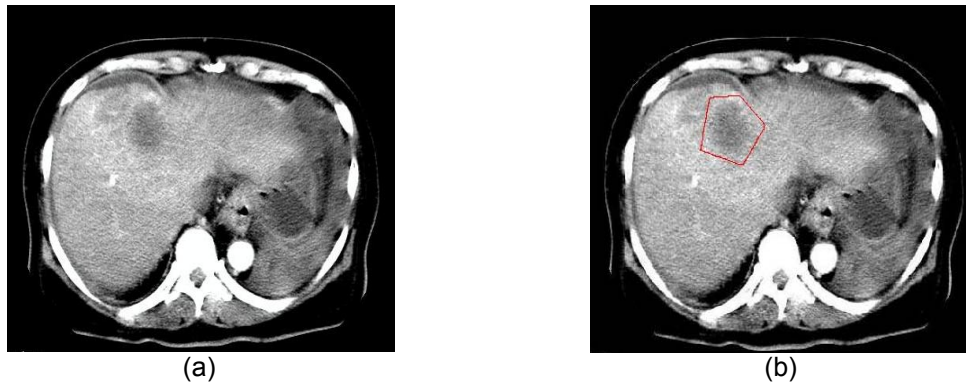


Figure 5. Low Density Lesion

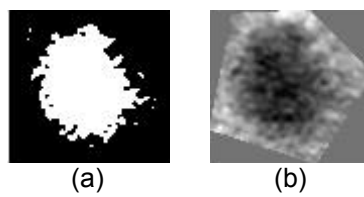


Figure 6. The Pre-segmentation

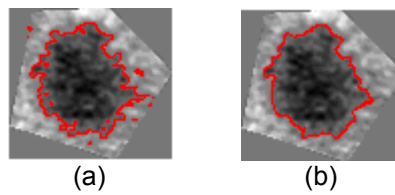


Figure 7. The Contour Line of Lesion

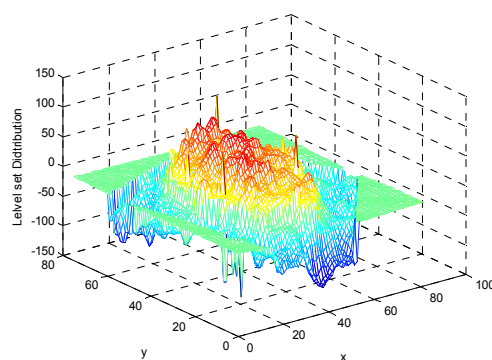


Figure 8. Level Set Distribution after 85 Iterations

The second is shown in Figure 5(a). There is a hypodense tumor, i.e. lower gray level in the centre of the liver. We select five points and construct a polygon to besiege the tumor, as shown in Figure 5(b). By using OTSU method pre-segment the image first, as shown in Figure 6(a). To decrease the gradient of the boundary of the polygon, we filled the empty area outside the polygon with the mean CT value of the liver, as shown in Figure 6(b). We can see that the initial contour shown in Figure 7(a) is near the boundary of the lesion, but there are some

dissociative areas inside or outside the tumor. Then the contour was evolved with the local level set method. The parameters are as follows: time-step  $Dt = 0.3$ ,  $m = 850$ ,  $l_1 = l_2 = 1$ . After 85 iterations, we got the final contour, as shown in Figure 7(b). The distribution of level set is shown in Figure 8. We can see that the contour is just on the boundary of the lesion.

**5. Image Registration for Locating Liver Lesion in other Phase Images**

Most HCCs are hypodense or isodense when visualized on plain CT images, as shown in Figure 9(b). Due to their predominant arterial supply, HCC are seen as transiently hyperdense masses in the arterial phase of hepatic enhancement as shown in Figure 9(a). They become isodense with hepatic parenchyma or hypodense in the portal venous phase of enhancement. On delayed images, the capsule and septa demonstrate prolonged enhancement, whereas contrast wash-out from the tumor makes the lesion again appear hypodense. So the HCC may be seen by eyesight when its dense differs from liver greatly and undetected when its dense is similar to liver [2]. If the liver lesion's density is similar to liver tissue, it is difficult to locate the lesion by segmentation. The only clue comes from the image of other phases. Because of influence of breath, the location of liver lesion may be different slightly. We use the image registration to align images of different phases.

Image registration is the process of overlaying two or more images of the same scene taken at different times, from different viewpoints, and/or by different sensors. It geometrically aligns two images—the reference and sensed images. The present differences between images are introduced due to different imaging conditions.

Registration methods can be categorized with respect to various criteria. The ones usually used are the application area, dimensionality of data, type and complexity of assumed image deformations, computational cost, and the essential ideas of the registration algorithm. In this paper we used Area-based methods. Area-based methods, sometimes called correlation-like methods or template matching [12] merge the feature detection step with the matching part. These methods deal with the images without attempting to detect salient objects. Windows of predefined size or even entire images are used for the correspondence estimation.

The classical representative of the area-based methods is the normalized Correlation  $r_{ij}$  in (12) and its modifications [13].

$$r_{ij} = \frac{\sum_x \sum_y (f(x,y) - \bar{f}(x,y)) (\tilde{f}_{ij}(x,y) - \bar{\tilde{f}}_{ij}(x,y))}{\sqrt{\sum_x \sum_y (f(x,y) - \bar{f}(x,y))^2 \sum_x \sum_y (\tilde{f}_{ij}(x,y) - \bar{\tilde{f}}_{ij}(x,y))^2}} \tag{12}$$

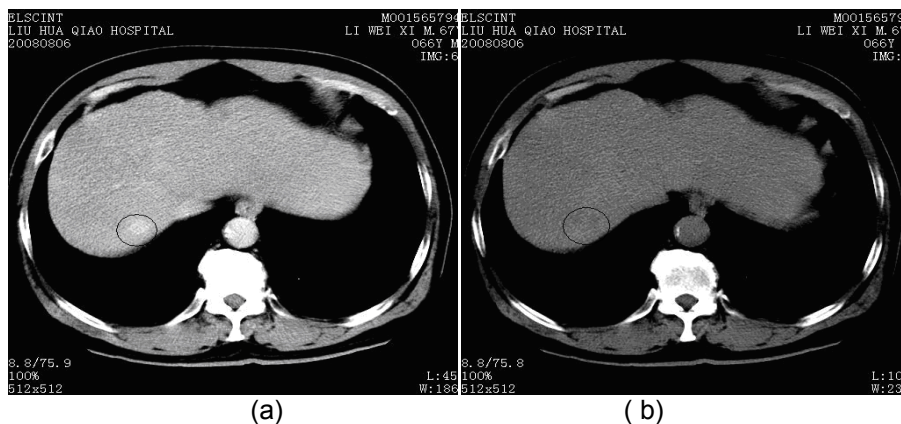


Figure 9. The SHCC Images

Where  $f(x,y)$  is the reference image,  $\bar{f}(x,y)$  is the average gray level of  $f(x,y)$  and  $f_{ij}(x,y)$  is the registered image which has been transformed,  $\bar{f}_{ij}(x,y)$  is the average gray level of the registered image.

This measure of similarity is computed for window pairs from the sensed and reference images and its maximum is searched. The window pairs for which the maximum is achieved are set as the corresponding ones.

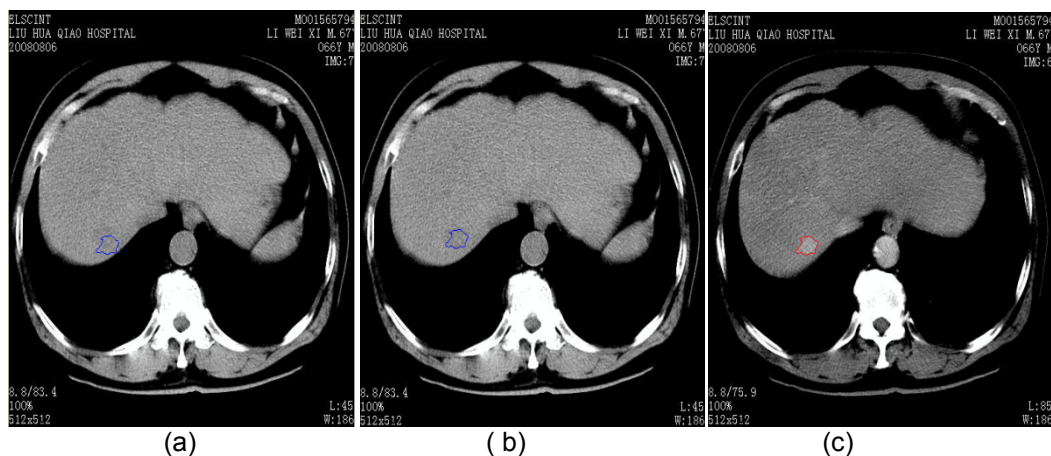


Figure 10. The Process of Image Registration

## 6. Experiment of Image Register

We tested the methods after segmenting the liver lesion with local level-set. The final contour of the SHCC is shown in Figure 10(a). The plain CT image, as shown in Figure, the gray level of the lesion is very close to the liver tissue, nearly undetectable. Before image registration, we mapped the region of the lesion into the plain CT image, as shown in Figure 10(b), we can see that the contour was migrated a little. We tried to align the plain CT image with the reference image. We translated the unregistered image to register it with the base image, and Correlation between the unregistered image and the reference image was computed. When its maximum is searched out, we got the registered image. The corresponding contour of lesion in the plain CT image was shown in figure 10(c). We can see that contour is on lesion's true location.

## 7. Conclusion

In this paper, we proposed comprehensive methods to locate liver lesions in CT multiphase images. It first segment liver lesion by combing local C-V level set algorithm, OTSU method in the CT images in which the lesion differs from liver tissue most markedly, then map the region of lesion into CT images of other phases by image registration. Because the contour evolves in the local area, the method can not only get rid of the interference of other organs, but also reduce the computational complexity. The results of experiments have testified the feasibility of the methods. We will apply other methods to segment the other lesion in our future work.

## Acknowledgements

This work was supported by scientific research fund of Hunan provincial education department (No. 11c0538) and Technology plan foundation of Hunan provincial, China (No. 2013FJ3058)



**References**

- [1] Yuanzhong Li, Shoji Hara, Kazuo Shimura. *A Machine Learning Approach for Locating Boundaries of Liver Tumors in CT Images*. Proceedings of the 18th International Conference on Pattern Recognition (ICPR). Hong Kong. 2006; 1: 400 – 403
- [2] E Rummeny, R Baro. *Imaging of Liver Diseases. Diseases of the Abdomen and Pelvis*. Davos: Springer. 2006.
- [3] Christiane Kulinna MD, Wolfgang Schima MD. *Imaging Features of Hepatic Metastases: CT and MR Diseases of The Abdomen and Pelvis*. Davos: Springer. 2006.
- [4] M Langer J, T Winterer, E Kotter, N Ghanem. Detection and characterization of benign focal liver lesions with multislice CT. *European Radiology*. 2006; 16(11): 2427-2443.
- [5] Seong-Jae Lim, Yong-Yeon Jeong, Yo-Sung Ho. Automatic Liver Segmentation for Volume Measurement in CT Images. *Journal of Visual Communication and Image Representation*. 2006; 17(4): 860-875.
- [6] S Mukhopadhyay, B Chanda. Multiscale morphological segmentation of gray-scale images. *IEEE Trans. Image Process*. 2003; 12(5): 533–549.
- [7] SJ Osher, JA Sethian. Fronts propagating with curvature dependent speed: Algorithms based on Hamilton-Jacobi formulations. *Comput Phys*. 1998; 79(1): 12-49.
- [8] XXu Jing, Chen Ken, Yang Xiangdong, Wu Dan. *Adaptive Level Set Method for Segmentation of Liver Tumors in Minimally Invasive Surgery Using Ultrasound Images*. Proceedings of the IEEE the 1st International Conference on Volume Bioinformatics and Biomedical Engineering (ICBBE). Wuhan. 2007; 1091-1094.
- [9] OTSU N. A threshold selection method from gray-level histograms. *IEEE Trans. Syst. Man Cybern*. 1979; 9(1): 62-66.
- [10] CHan TF, Vese LA. Active contours without edges. *IEEE Transactions on Image Processing*. 2001; 10(2): 266-277.
- [11] JJinsheng Xiao, Lingling Xu, Benshun Yi. *The Improvement of C-V Level Set method for Image Segmentation*. Proceedings of the 2008 International Conference on Computer Science and Software Engineering (CSSE). Wuhan. 2008; 2: 1106-1109.
- [12] LMG Fonseca, BS Manjunath. Registration techniques for multisensor remotely sensed imagery. *Photogrammetric Engineering and Remote Sensing*. 1996; 562(9): 1049–1056.
- [13] BBarbara Zitová, Jan Flusser. Image registration methods: a survey. *Image and Vision Computing*. 2003; 21(11): 977–1000