A MODIFIED DISTANCE REGULARIZED LEVEL SET MODEL FOR LIVER SEGMENTATION FROM CT IMAGES

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ABSTRACT

Segmentation of organs from medical images is an active and interesting area of research. Liver segmentation incurs more challenges and difficulties compared with segmentation of other organs. In this paper we demonstrate a liver segmentation method for computer tomography images. We revisit the distance regularization level set (DRLS) model by deploying new balloon forces. These forces control the direction of the evolution and slow down the evolution process in regions that are associated with weak or without edges. The newly added balloon forces discourage the evolving contour from exceeding the liver boundary or leaking at a region that is associated with a weak edge, or does not have an edge. Our experimental results confirm that the method yields a satisfactory overall segmentation outcome. Comparing with the original DRLS model, our model is proven to be more effective in handling over-segmentation problems.

KEYWORDS

Liver segmentation, level set method, Distance Regularized Level Set (DRLS) model, and balloon forces

1. INTRODUCTION

Human liver constitutes one of the most prominent organs. The liver is one of the most important organs in the human body. The liver is located in the upper right quadrant of the abdominal cavity and is the largest organ in the body. The liver has a weight of about 2% or 3% to the total body weight [1]. The liver is an unshaped organ since its shape is mainly determined by the surrounding structures such as the lower ribs and the diaphragm. The liver can be small and only located in the right half part of the abdomen or extend all to the left and cover the spleen [2].

The volume of a healthy liver correlates to the individually required organ functions when a liver grows during childhood and adolescence; it adapts to the needs and increases in size. Later, when an adult gains or loses weight, the organ will also change to match the new metabolic demand. It performs several key functions in the human body. Beside its main purpose as a filter for blood and a store for minerals and vitamins, other duties of the liver include separating bile and

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proteins, processing of sugar and decompositions of medications. Unfortunately, the liver is prone to many life-threatening diseases, most notably, hepatitis C, cirrhosis, and cancer.

During the last few years, computer-aided surgical planning systems (CAD) have contributed significantly in diagnosing and treatment of liver diseases[3]. These cutting-edge methods portray the structure of liver and its vessels often in the form of 3D visualizations, provide insights into surgical simulations with cutting guidelines. This in turn leads to a significantly shorter planning time. On this regard, accurate segmentation of a liver from its surrounding organs in compute tomography (CT) images represents one of the most daunting tasks.

Developing an effective method to segment liver from CT images is a daunting task. This is primarily due to the very similar intensity values between the liver and its adjacent organs, the complexity in the geometrical structure of the liver, significant variations in shape and volume of liver between individuals, and the injection of contrast media. Several artefacts of pulsation and motion, and partial volume effects also contribute the difficulties encountered in carrying out automatic liver segmentation in CT images. It follows that liver segmentation from medical images is an active area of research.

Methods and approaches utilized in liver segmentation in the CT images are generally categorized into two main classes: semiautomatic and fully automatic liver segmentation methods. Semi-automatic liver segmentation methods entail a rather limited user intervention to complete the task. This intervention may vary from a manual selection for seed points to a manual refinement of a binary mask for the liver. The term “fully automated” denotes a liver segmentation process that is implemented without any intervention by an operator. This property is regarded as a benefit of fully automated methods as it saves processing times and causes results to be free from any errors and biases that may be introduced by the intervention of the user.

Herein, we survey recent advances in methods used in liver segmentation. These methods fall in three main categories; namely, gray level based methods, model based methods, and texture based methods [4]. It is apparent that each category of liver segmentation methods has its own advantages and shortcomings. It follows that some methods may perform well in certain applications while fail poorly on other cases.

The gray level based methods [5-15] deploy features from an image directly. Consequently, gray level based methods are widely used in liver segmentation. These methods rely mainly on the evolution of gray level toward targets. Whilst gray level methods are generally fast, the presence of changes in gray level intensity of targets may affect their performance. Despite of using prior knowledge, success of gray level methods is significantly hindered if the liver occupies a small percentage of the image. Gray level is applied either manually or via an automatic rough segmentation. The purpose of these two procedures is to gather information germane to the gray level. The profound reliability of these methods is often over shadowed by their time-expensive nature. In most cases, gray level methods necessitate substantial computational time.

Several gray level based methods utilises gradient information as a well-defined approach to deal with image boundaries. However, this approach becomes impractical upon the presence of numerous boundaries. Under these conditions, gray level based methods may readily converge to wrong boundaries, resulting in over- or under segmentation. This could be corrected by refining the results through manual work or via the implementation of other methods.

On the contrary, structure based methods [16-20] can generally handle cases with unclear liver boundaries by utilising prior knowledge. Structure based methods can carry out tasks that could not be performed by gray level based methods. However, these methods involve a great deal of training data to cover all plausible conditions of the liver. Applying these methods hold profound difficulty when handling non-standard liver's shapes for the liver. In other words, it is very hard to develop a "universal" segmentation model for liver based on structure based methods.

Instead of using gray level or shapes, texture based methods [21-24] utilises pattern recognition and machine learning in their search for boundaries. As a result, these methods enable one to collectively consider more features. Texture based methods can produce better results even when the boundaries of liver are not clear. An accurate account of texture feature represents one of the main challenges in these methods, in addition to the need for training data. Furthermore, selecting a proper descriptor out of many, poses another problem. It is worthwhile noting that both machine learning and pattern recognition still incur much weak processing ability if compared with human brain and they are not able to achieve good segmentation result without the use of other refined methods.

In most practical applications, gray level based methods often provide rather good segmentation results. Structure based methods are mainly based on the shape of the object, a characteristic affording them powerful performance. Methods that use texture properties work to simulate processes in human's brain. On the other hand, level set methods have been widely used in segmentation of medical images [25-27]. Despite of their wide and effective uses, successful application of level set relies heavily on the initial position.

Level set methods generally attain satisfactory if the initial contour is positioned near the target. 3D liver segmentation methods can be grouped into two classes, namely, direct 3D segmentation and propagation of the 2D slice-based segmentation. In the first group, a 3D deformable surface is first initialised in multiple 2D slices of the liver. This is followed by automatically updating the initial 3D mesh by means of forces characterized by the image gradient and the smoothness of the contour. As a result, direct 3D segmentation is time consuming and requires many user interactions. This may render outcomes to be dependent on the user choices.

The second class of 3D liver segmentation stems from the slice-based propagation approach. In this method, the 3D CT images are re-sliced into a number of 2D slices. A 2D segmentation is applied on each slice that is initialized by a propagated boundary from the previous 2D slice. As such, this technique reduces a 3D segmentation problem to a sequence of 2D segmentation problems. Each of the reduced 2D segmentation sub-problems is significantly less sophisticated than the original 3D segmentation problem. Furthermore, it is computationally less expensive to integrate 2D shape information - as a shape constraint - into the 3D segmentation procedure. Because the difference between adjacent slices is minimal, the final contour of one slice can potentially afford useful information with regard to the initial contour position, prior intensity, and shape information. Acquiring prior knowledge pertinent to these aforementioned factors enhances the segmentation performance of the level set method of the following slices.

Our main contribution in this paper is to revisit the distance regularization level set [28] (DRLS) model by deploying new balloon forces. These forces control the direction of the evolution and slow down the evolution process in regions that are associated with weak or without edges. We organise this contribution as follows, in Section 2 we present the DRLS model. Section 3

demonstrates our adapted theoretical approach. Section 4 depicts selected experimental results, and finally concluding remarks are presented in Section 5.

2. DISTANCE REGULARIZED LEVEL SET METHOD

Li *et al.* [28] proposed a level set method termed as Distance Regularized Level Set (DRLS) model. The DRLS model uses an edge-based active contour method to drive the level set function (LSF) to the desired boundary, and provides a simple and efficient narrowband implementation without re-initialization.

Let $\phi : \Omega \to \Re$ be a level set function defined on domain Ω. An energy function $\varepsilon(\phi)$ is defined as:

$$\varepsilon(\phi) = \beta R_p(\phi) + \varepsilon_{ext}(\phi) \tag{1}$$

where $\beta > 0$ is a constant and $R_p(\phi)$ is the level set regularization term, defined by

$$R_p(\phi) = \int_{\Omega} p(|\nabla\phi|)dx \tag{2}$$

where p signifies an energy density function $p : [0,\infty) \to \Re,$ defined as

$$p(s) = \begin{cases} \frac{1}{2}(s-1)^2, & \text{if } s \le 1 \\ \frac{1}{(2\pi)^2}(1-\cos(2\pi s)), & \text{otherwise} \end{cases} \tag{3}$$

The minimization of the energy $\varepsilon(\phi)$ can be achieved by solving a level set evolution equation. For a LSF, an external energy function is defined by

$$\varepsilon_{ext}(\phi) = \lambda L_g(\phi) + \alpha A_g(\phi), \tag{4}$$

where λ and α are the coefficient of the length term $L_g(\phi)$ and area term $A_g(\phi)$, which is given by

$$L_g(\phi) = \int g\delta_\varepsilon(\phi)|\nabla\phi|dx \tag{5}$$

and

$$A_g(\phi) = \int gH(-\phi)dx \tag{6}$$

where $g \in [0,1)$ is an edge indicator function given by

$$g = \frac{1}{1+\left|\nabla G_\sigma * I\right|^2}, \tag{7}$$

where G_σ is a Gaussian kernel with a standard deviation σ, and I is the input image. The Dirac delta function δ_ε and Heaviside function H_ε in Eqs. (5) and (6) are approximated by the following smooth function δ_ε and H_ε, respectively, as in many level set methods:

$$\delta_\varepsilon(s) = \begin{cases} \frac{1}{2\varepsilon}[1+\cos(\frac{\pi t}{\varepsilon})], & \text{if } |t| \le \varepsilon \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

and

$$H_\varepsilon(s) = \begin{cases} \frac{1}{2}(1+\frac{t}{\varepsilon}+\frac{1}{\pi}\sin(\frac{\pi t}{\varepsilon})), & \text{if } |t| \le \varepsilon \\ 0, & \text{if } t < -\varepsilon \\ 1, & \text{if } t > \varepsilon \end{cases} \tag{9}$$

where ε is a constant, typically set to 1.5. The length term $L_g(\phi)$ was first introduced by Caselles *et al.* [29] in their proposed geodesic active contour (GAC) model. $L_g(\phi)$ is the line integral of the function g along the zero level contour of ϕ, which is minimized when the zero level set of ϕ is located at the object boundaries which in turn keeps the curve smooth during the deformation.

The area term $A_g(\phi)$ calculates the weighted area inside the evolving contour. It is introduced to speed up the motion of the zero level contour when the contour is far away from the desired object boundaries and slow down the expanding and shrinking of the zero level contour when it arrives at object boundaries where g is smaller. $A_g(\phi)$ represents a balloon forces in which the sign of α controls the direction of the level set evolution (shrinking or expanding). The level set evolution equation in the DRLS model is defined by:

$$\frac{\partial \phi}{\partial t} = \beta.\mathrm{div}(d_p(|\nabla \phi|)\nabla \phi) + \delta(\phi).\lambda.\mathrm{div}\left(g\frac{\nabla \phi}{|\nabla \phi|}\right) + \delta(\phi).\alpha.g \tag{10}$$

The problem with the DRLS model in the case of liver segmentation is that the curve will evolve and deviate from the liver boundary in the region with weak or without edges. In this contribution, we will modify the distance regularization level set method [28] (DRLSM) by adding a new balloon force to guide the evolution process and discourage the evolving contour from leaking at a region with a weak or without an edges and from going far from the liver boundary.

3. THE PROPOSED MODEL

In this paper, we propose a new balloon force that controls the direction of the evolution and slows down the evolving contour at weak or blurred edges. Since the liver has a very similar intensity with its adjacent organs, this could easily result in over and/or under segmentation results. The DRLS model does not perform well with liver segmentation.

We will modify the DRLS model to segment the liver contour in each 2D slice by using a new balloon force that controls the direction of the evolution and slows down the evolution process in the region with weak or without edges, which subsequently discourage the evolving contour from leaking at a region with a weak or without an edge and from deviating from the liver boundary. Our balloon term will be built using the probability density function. The methodology encompasses steps described in the following sections.

3.1 PRE-PROCESSING

The intensity distribution of the liver is irregular due to noises, so liver segmentation without pre-processing is difficult. A smoothing step, in theory, would make the intensity distribution less variable. In our work, a Gaussian filter is used as a smoothing step.

3.2 SEGMENTATION OF THE REFERENCE SLICE

This step is the most important step in our 3D liver segmentation method. The segmented liver contour will be the initial contour for the adjacent slice so the segmentation result should be accurate. The starting slice or the reference slice can be selected as the middle or the largest slice of the liver volume. In this contribution we used the Active Shape Model (ASM) [30] to segment the reference slice.

3.3 2D SLICE BASED PROPAGATION APPROACH

Since the variation of shape and intensity between the adjacent slices are very small we can use these information from the previous slice to segment the next slice. In our method we compute the mean μ intensity and the σ variance of the segmented slice. According to [31], about 98% of liver $[\mu-3\sigma,\mu+3\sigma]$. pixel is located in $[\mu-3\sigma,\mu+3\sigma]$. Generating an evolution region by expanding the previous segmented slice by a number of pixels and compute the probability density function inside this region using the following equations:

$$B(X)=\begin{cases}\dfrac{1}{\sigma\sqrt{2\pi}}e^{-\frac{1}{2}(\frac{x-\mu}{\sigma})^2}, & \text{if } x\in[\mu-3\sigma,\mu+3\sigma]\\ 0, & \text{otherwise}\end{cases} \tag{11}$$

We then shrink the previous segmented slice and use it as the initial contour for its adjacent slices in both directions.

3.4 MODIFIED DRLS MODEL

Since the liver boundary to be segmented is not far from the contour propagated from the previous slice, a shape and intensity prior information will discourage the evolving contour from leaking at a region with a weak edge or without an edge. We have modified the DRLSM by adding the probability density energy term to the evolution equation and use it as a balloon forces to control the direction and the speed of the evolution process

$$E(\phi) = \rho.R_P(\phi) + \lambda.L_g(\phi) + \alpha.B(\phi) \tag{12}$$

where ρ, λ and α are the coefficients of the regularization term, the length term, and the probability term, respectively. This energy functional can be minimized by solving the following gradient flow:

$$\frac{\partial \phi}{\partial t} = \rho.\mathrm{div}(d_p(|\nabla\phi|)\nabla\phi) + \delta_\varepsilon(\phi).\lambda.\mathrm{div}\left(g\frac{\nabla\phi}{|\nabla\phi|}\right) + \delta_\varepsilon(\phi).\alpha.B(\phi) \tag{13}$$

The above procedure is repeated until the contours in all 2D slices of the 3D image are segmented. A 3D liver surface is reconstructed from the contours segmented from all 2D slices.

4. RESULT AND DISCUSSION

In the DRLS model, two segmentation stages are applied. The first stage is for evolving the contour in the direction of the object boundary, speeding up the evolution process when the evolving contour is far from the object boundary and slowing down the evolution process when the evolving contour is close to the object boundary. The second stage concerns with the refinement of the segmentation results. In each experiment, we selected values of ρ, λ and α to be 0.02, 5 and -1 for the first stage and 0.02, 5 and 0 for the second stage, respectively. The zero level set is initialized as a binary function and evolves according to the evolution equation Eq. (13) for our model and Eq. (10) for the DRLS model.

Figure 1 presents segmentation results of the DRLS model and the proposed model in a liver CT slice. Our model performs well and gives a satisfactory result comparing to the DRLS model. The DRLS model fails to segment the liver boundary and the evolving contour leaks from the region with weak edges. Our balloon force slows down the evolution process close to the liver boundary and stops the evolving contour from going far in the region with weak or without edges. Comparing with the DRLS model, our model is more effective in dealing with over segmentation problem.

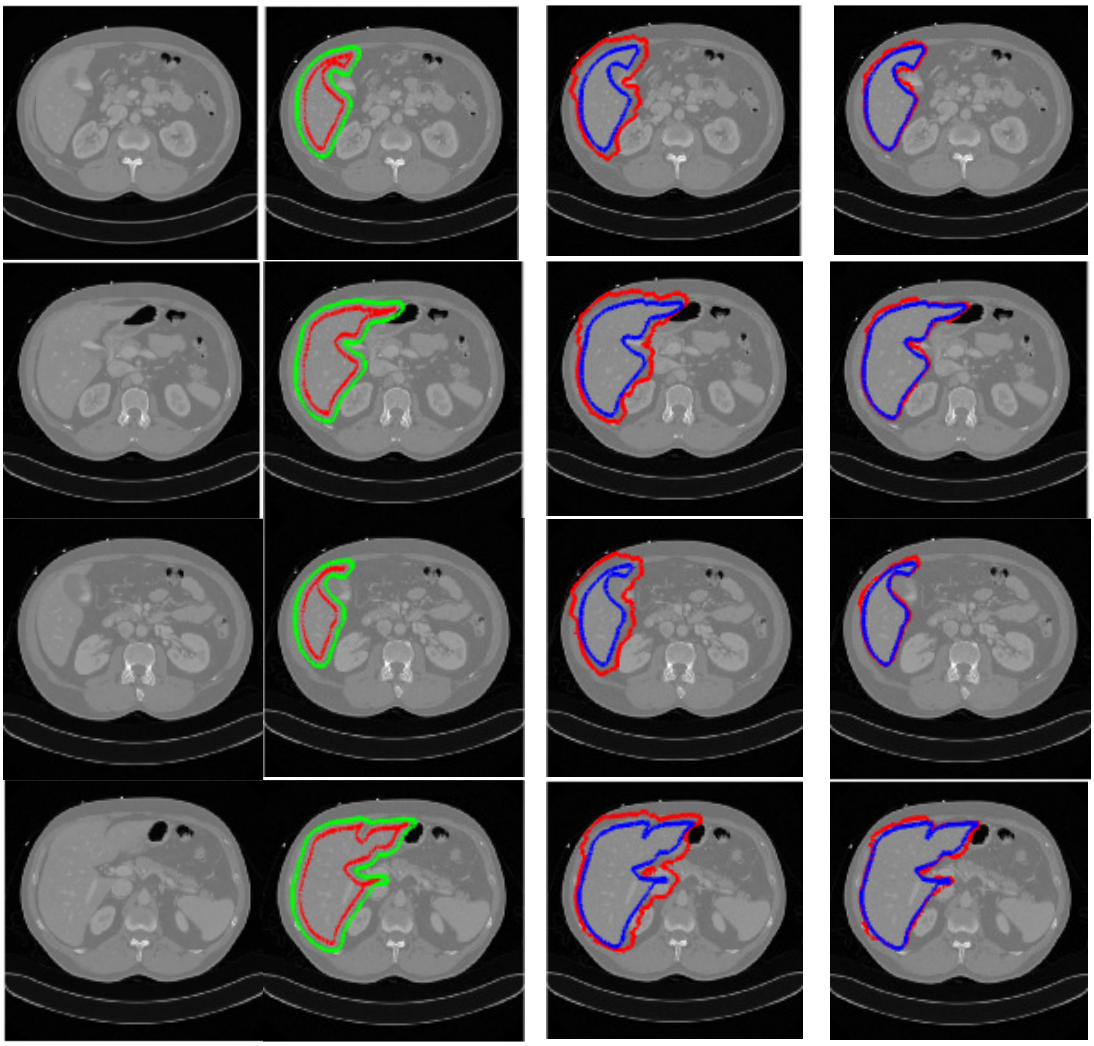

Figure 1. Comparisons of liver segmentation results between the DRLS model and the proposed method. The first column shows the liver slice in a CT scan; the second column shows the evolving region in green and the initial contour in red. The third column shows the ground truth segmented manually by a radiologist in blue and the final segmentation result of the DRLS model in red and the fourth column shows the ground truth segmented manually by the radiologist in blue and the final segmentation result with our proposed method in red.

Figure 2 shows some examples of liver extraction results based on our proposed method. We tested our model on a liver dataset containing 10 volumes of abdominal CT images. Each volume has 64 slices and the size of each slice is 512x512 pixels. Each slice in the dataset is provided with corresponding ground truth segmented manually by a radiologist. The model deals very well with over segmentation problems. Our model can handle the over segmentation problem very well in comparison with the DRLS model that is not able to handle this task well.

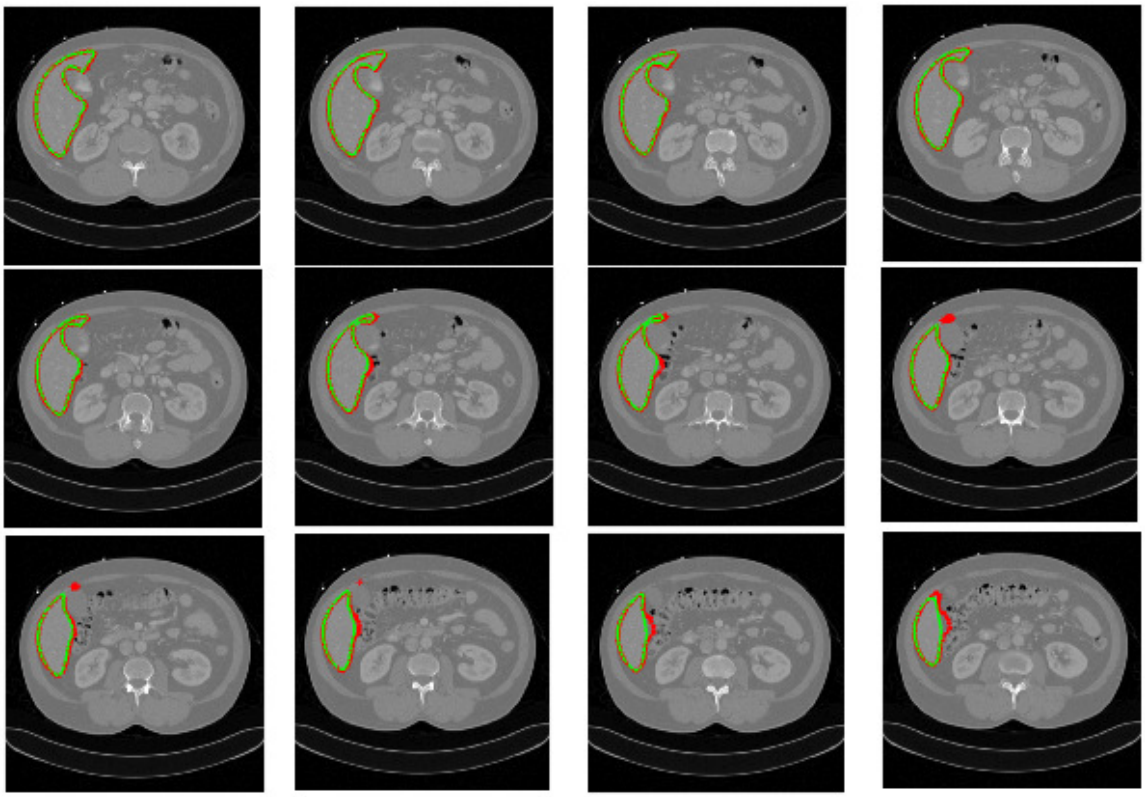

Figure 2. The experimental result of our proposed method on a sequence of liver slices for one person. The green and red colours refer to the ground truth segmented manually by the radiologist and the final segmentation result of our proposed method, respectively.

5. CONCLUSION

In a nutshell, the original DRLS model is modified by adding a novel balloon force. The most advantageous feature of our method stems from its ability to guide the direction of the evolving contour via several desired approaches. Our model slows down the evolving contour in regions with blurred edges and dampens the evolving contour from exceeding boundaries of liver. Experimental results have shown that our method produces satisfactory outcome, especially when dealing with over-segmentation problems comparing with the DRLS model.

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REFERENCES

[1] J. E. Skandalakis, L. J. Skandalakis, P. N. Skandalakis, and P. Mirilas, "Hepatic surgical anatomy,"Surgical Clinics of North America, vol. 84, pp. 413-435, 2004.

[2] A. Schenk, "Liver Segmentation and Its Application to Hepatic Interventions," PhD, 2012.

[3] K. J. Mortelé, V. Cantisani, R. Troisi, B. de Hemptinne, and S. G. Silverman, "Preoperative liver donor evaluation: imaging and pitfalls," Liver Transplantation, vol. 9, pp. 6-14, 2003.

[4] S. Luo, X. Li, and J. Li, "Review on the Methods of Automatic Liver Segmentation from Abdominal Images," Journal of Computer and Communications, vol. 2, pp. 1-7, 2014.

[5] A. Beck and V. Aurich, "Hepatux–a semiautomatic liver segmentation system," 3D Segmentation in The Clinic: A Grand Challenge, pp. 225-233, 2007.

[6] R. Pohle and K. D. Toennies, "Segmentation of medical images using adaptive region growing," Medical Imaging vol. 4322, pp. 1337-1346, 2001.

[7] S. Kumar, R. Moni, and J. Rajeesh, "Automatic liver and lesion segmentation: a primary step in diagnosis of liver diseases," Signal, Image and Video Processing, vol. 7, pp. 163-172, 2013.

[8] C. Platero, J. M. Poncela, P. Gonzalez, M. C. Tobar, J. Sanguino, G. Asensio, et al., "Liver segmentation for hepatic lesions detection and characterisation," Biomedical Imaging: From Nano to Macro, pp. 13-16, 2008.

[9] D. A. B. Oliveira, R. Q. Feitosa, and M. M. Correia, "Liver Segmentation using Level Sets and Genetic Algorithms," VISAPP vol. 2, pp. 154-159, 2009.

[10] H. Yang, Y. Wang, J. Yang, and Y. Liu, "A novel graph cuts based liver segmentation method," Medical Image Analysis and Clinical Applications (MIACA), pp. 50-53, 2010.

[11] Y.-W. Chen, K. Tsubokawa, and A. H. Foruzan, "Liver segmentation from low contrast open MR scans using k-means clustering and graph-cuts," in Advances in Neural Networks, ed: Springer, 2010, pp. 162-169.

[12] A. H. Foruzan, C. Yen-Wei, R. A. Zoroofi, A. Furukawa, H. Masatoshi, and N. TOMIYAMA, "Segmentation of Liver in Low-Contrast Images Using K-Means Clustering and Geodesic Active Contour Algorithms," IEICE TRANSACTIONS on Information and Systems, vol. 96, pp. 798-807, 2013.

[13] R. Adams and L. Bischof, "Seeded region growing," Pattern Analysis and Machine Intelligence, IEEE Transactions on, vol. 16, pp. 641-647, 1994.

[14] K. Suzuki, R. Kohlbrenner, M. L. Epstein, A. M. Obajuluwa, J. Xu, and M. Hori, "Computer-aided measurement of liver volumes in CT by means of geodesic active contour segmentation coupled with level-set algorithms," Medical physics, vol. 37, pp. 2159-2166, 2010.

[15] B. N. Li, C. K. Chui, S. Chang, and S. H. Ong, "Integrating spatial fuzzy clustering with level set methods for automated medical image segmentation," Computers in Biology and Medicine, vol. 41, pp. 1-10, 2011.

[16] J. Liu and J. K. Udupa, "Oriented active shape models," Medical Imaging, IEEE Transactions on, vol. 28, pp. 571-584, 2009.

[17] T. Heimann, I. Wolf, and H.-P. Meinzer, "Active shape models for a fully automated 3D segmentation of the liver–an evaluation on clinical data," in Medical Image Computing and Computer-Assisted Intervention–MICCAI ed: Springer, 2006, pp. 41-48.

[18] M. Erdt, S. Steger, M. Kirschner, and S. Wesarg, "Fast automatic liver segmentation combining learned shape priors with observed shape deviation," in Computer-Based Medical Systems (CBMS), 2010, pp. 249-254.

[19] H. Badakhshannoory and P. Saeedi, "A model-based validation scheme for organ segmentation in CT scan volumes," Biomedical Engineering, IEEE Transactions on, vol. 58, pp. 2681-2693, 2011.

[20] S. Martin, J. Troccaz, and V. Daanen, "Automated segmentation of the prostate in 3D MR images using a probabilistic atlas and a spatially constrained deformable model," Medical physics, vol. 37, pp. 1579-1590, 2010.

[21] W. Huang, Z. Tan, Z. Lin, G. Huang, J. Zhou, C. Chui, et al., "A semi-automatic approach to the segmentation of liver parenchyma from 3D CT images with Extreme Learning Machine," Engineering in Medicine and Biology Society (EMBC, pp. 3752-3755, 2012.

[22] M. Danciu, M. Gordan, C. Florea, and A. Vlaicu, "3D DCT supervised segmentation applied on liver volumes," Telecommunications and Signal Processing (TSP) pp. 779-783, 2012.

[23] S. Luo, X. Li, and J. Li, "Improvement of Liver Segmentation by Combining High Order Statistical Texture Features with Anatomical Structural Features," Engineering, vol. 5, pp. 67-72, 2013.

[24] S. Luo, Q. Hu, X. He, J. Li, J. S. Jin, and M. Park, "Automatic liver parenchyma segmentation from abdominal CT images using support vector machines," Complex Medical Engineering, CME, pp. 1-5, 2009.

[25] C. Xu, d. l.pham, and j. l.prince, "Medical Image Segmentation Using Deformable Models," in SPIE Handbook on Medical Imaging vol. 3, J. M. Fitzpatrick and M. Sonka, Eds., ed, 2000, pp. 129-174.

[26] N. M. Altarawneh, S. Luo, B. Regan, C. Sun, and F. Jia, "Global threshold and region-based active contour model for accurate image segmentation," Signal & Image Processing: An International Journal (SIPIJ), vol. 5, pp. 1-11, 2014.

[27] N. M. Altarawneh, S. Luo, B. Regan, and C. Sun, "A novel global threshold-based active contour model," presented at the Second International Conference on Signal, Image Processing and Pattren Recognition (SIPP), Sydney, 2014.

[28] C. Li, C. Xu, C. Gui, and M. D. Fox, "Distance regularized level set evolution and its application to image segmentation," Image Processing, IEEE Transactions on, vol. 19, pp. 3243-3254, 2010.

[29] V. Caselles, R. Kimmel, and G. Sapiro, "Geodesic active contours," International journal of computer vision, vol. 22, pp. 61-79, 1997.

[30] B. Van Ginneken, A. F. Frangi, J. J. Staal, B. M. ter Haar Romeny, and M. A. Viergever, "Active shape model segmentation with optimal features," medical Imaging, IEEE Transactions on, vol. 21, pp. 924-933, 2002.

[31] X. Li, S. Luo, and J. Li, "Liver Segmentation from CT Image Using Fuzzy Clustering and Level Set," Journal of Signal and Information Processing, vol. 4, pp. 36-42, 2013.

[32] N. M. Altarawneh, S. Luo, B. Regan, and C. Sun, "liver segmentation from ct imaged using a modified distance regularized level set method based on a novel balloon forces," presented at the International Conference on Signal, Image processing and Multimedia(SPM), Sydney, 2015.