UTERINE FIBROID SEGMENTATION ON MRI BASED ON CHAN-VESE LEVEL SET METHOD AND SHAPE PRIOR MODEL

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Abstract: Uterine fibroid the most common benign tumor of the female pelvic affected 20%- 50% of the women in the world. The efficacy of medical treatment is gauged by shrinkage of the size of these tumors after surgery. Complex fibroids anatomy, nonhomogeneity region and missing boundary in some cases are a challenging task in the segmentation. In this paper, we present a method to robustly segment these fibroids on MRI and measure the volume. Our method is based on combination of two step Chan-Vese level set method and geometric shape prior model. With calculating an initial region inside the fibroid using Chan-Vese level sets method, rough segmentation obtained followed by a prior shape model. We found the algorithm efficient and that it has some good results.

1 INTRODUCTION

Magnetic resonance image (MRI) is widely used in radiology diagnosis especially in soft tissues. Different modalities like T1, T2 and FLAIR and the fusion of information provided by them can be useful in diagnosis. One of the recent applications of MRI is to diagnosis uterine fibroid. As the uterine fibroid is the most common benign tumors of the female pelvic (VeKaut, 1993), MR imaging can be very useful in follow-up the patient condition, diagnosis and treatment process (Cura and Bugnone, 2006). Uterine segmentation and volume measurement is one of the important tasks that usually is a time consuming and inaccurate work when is performed manually. By automated and semi-automated segmentation techniques we can assist physicians to have a more accurate result and a fast process. In (Guyon et al.,2003) geodesic active contours and fast marching level set have been used for segmenting fibroid and rigid landmark registration has been applied for tracking its variation over time. In (Jianhua et al, 2006) fast marching level set has been used for initial segmentation and Laplacian level set has been applied to refine the segmentation result. These methods can perform only in homogeneous and connected boundary regions.

Even with great advantages of level set based methods, active contours that are based on image gradients are highly sensitive to the presence of noise, poor image contrast and missing boundaries. These lead to bad segmentation results. To overcome these problems, some methods have proposed robust region-based evolution criteria into active contour energy function, built from intensity statistics and homogeneity requirements (Paragios and Deriche, 2002; Chan andVese, 2001). Prior knowledge is usually very helpful to segment or localize an anatomical structure. Several methods have been proposed to incorporate prior shape information into boundary determination. (Cootes et al, 1995) have proposed an active shape model to construct a statistical shape model from a set of training images for image segmentation. The model is built by outlining the contours and finding point correspondences across shapes. (Staib and Duncan,

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1992) incorporate global shape information into the segmentation process by using an elliptic Fourier decomposition of the boundary and placing a Gaussian prior on the Fourier coefficients. (Leventon, 2000) incorporate statistical shape influence into the evolution process of geodesic active contours (Caselles, 1997) by attracting the evolving contour toward the shape priors. The correspondence problem is solved in their approach by embedding the prior shape as the zero level set of a level set function map. (Chen et al, 2001) propose a variational method that minimizes an energy function defined by the image gradients and the shapes of interest. (Bresson et al., 2006) propose a method by combination of region, boundary and shape features based on Mumford-Shah function (Mumford and Shah, 1989), level set approach and prior shape model that is based on PCA of training data to robustly segmentation.

In this paper we propose a tow step method for robustly segmentation of uterine fibroids. First raw segmentation obtained using Chan-Vese level set method based on Mumford-Shah function. Then segmentation is refined by applying prior shape model using Bresson et al, method. In the proposed method, the previous training data is not required. We generate training data from ellipses model of the segmented region.

In section 2 we describe the first step prior segmentation using Chan-Vese level set method. Section 3 explains the segmentation refinement based on Bresson et al. prior shape model. Section 4 presents the segmentation results obtained by the proposed approach. Section 5 presents some conclusions and future extensions to this approach.

2 INITIAL SEGMENTATION BASED ON CHAN-VESE LEVEL SET METHOD

All classical snakes and active contour models are based on edge-function depending on the image gradient. These models can detect only objects with edges defined by gradient to stop the curve evolution. In practice, the discrete gradients are bounded and then the stopping function is never zero on the edges and algorithm fail to segment region.

(Chan and Vese, 2001) proposed a different active contour method, that is not based on the gradient of the image for the stopping process. The stopping term is based on Mumford–Shah segmentation techniques (Mumford and Shah, 1989).

The Mumford–Shah function for segmentation is:

$$\begin{aligned} F^{MS}(u,c) &= \mu.Length(C) \\ &+ \lambda\int_{\Omega} u_0(x,y) - u(x,y)|^2\ dxdy \\ &+ \int_{\Omega\backslash C} |\nabla u(x,y)^2 dxdy \end{aligned} \quad (1)$$

Where $u_0 : \Omega \to R$ is a given image, μ and λ are positive parameters. Their active contour model is a particular case of the minimal partition problem, in which they look for the best approximation u of u_0, as a function taking only two values, namely and with one edge C, represented by the snake or the active contour. This particular case of the minimal partition problem can be formulated and solved using the level set method (Osher and Sethian 1988).

$$u = \begin{cases} average(u_0) & insideC \\ average(u_0) & outsideC \end{cases} \quad (2)$$

Associated Euler–Lagrange equation deduced for ϕ represented in equation 3 which parameterize the descent direction by an artificial time $t \geq 0$. The equation $\phi(t,x,y)$ (with $\phi(0,x,y) = \phi_0(x,y)$) defining the initial contour is:

$$\begin{aligned} &\frac{\partial\phi}{\partial t} = \delta_e(\phi)[\mu\ \ div(\frac{\nabla\phi}{\nabla\phi}) - v - \lambda_1(u_0 - c_1)^2 \\ &+ \lambda_2(u_0 - c_2)^2] = 0 \qquad in(0,\infty)\times\Omega \\ &\phi(0,x,y) = \phi_0(x,y) \qquad in\Omega \\ &\frac{\delta_e(\phi)}{|\nabla\phi|}\frac{\partial\phi}{\partial n} = 0 \qquad on\partial\Omega \end{aligned} \quad (3)$$

In uterine fibroids that have a calcified and infarcted region, edge based method fail to segment whole region. We applied this method to the images for initial segmentation. The segmentation is then performed in whole image with initial manual region in first slice. Figure.1 shows segmentation result in some steps for a sample image.

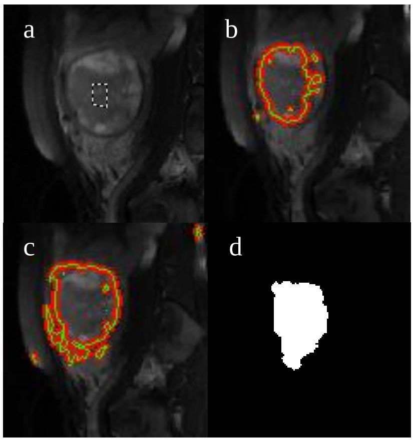

Figure 1: Result of applying Chan-Vese method, a: Initial manual contour in the region, b and c: Evolving level set to region boundary, d: Final segmentation result.

3 SEGMENTATION REFINMENT USING ACTIVE PRIOR SHAPE MODEL

The shape prior can be defined by different models such as Fourier descriptors, medial axis or atlas-based parametric models. Recently, the level set representation of shapes has been employed as a shape model (Leventon et al., 2000; Paragios et al., 2003; Charpiat et al., 2003). This shape description presents strong advantages since parameterization free. It can represent shapes of any dimension such as curves, surfaces and hyper-surfaces and basic geometric properties such as the curvature. Finally, this shape representation is also naturally consistent with the level set framework of active contours. In (Leventon et al, 2000), authors have used a level set representation to model the shape prior. They have defined a shape model of the object of interest by computing principal components analysis (PCA) of training shapes embedded in level set functions. They have then integrated this shape model in an evolution equation to globally drive the active contour towards the prior shape. However, their evolution equation is not expressed by a partial differential equation (PDE) and there is no variational formulation associated with his evolution equation.

Recently Bresson et al, have proposed a variational approach following the energy functional model of (Chen et al. 2002) where integrate the shape prior of (Leventon et al, 2002). They added a region-based energy term based on the Mumford-Shah function (Mumford and Shah, 1989) to improve the robustness of segmentation model with respect of noise, poor image contrast and initial position of the contour.

They proposed the following energy functional to address the problem of object segmentation using a geometric shape prior with local and global image information:

$$F = \beta_s F_{shape}(C, X_{pca}, X_T) + \beta_b F_{boundary}(C) + \beta_r F_{region}(X_{pca}, X_T, u_{in}, u_{out}) \quad (4)$$

With

$$F_{shape} = \oint_0 \hat{\phi}(x_{pca}, h_{x_T}(C(q)))|C'(q)|dq \quad (5)$$

$$F_{boundary} = \oint_0 g(|\nabla I(C(q))|)|C'(q)|dq \quad (6)$$

$$F_{region} = \int_{\Omega_{in(X_{pca},X_T)}} (|I-u_{in}|^2 + \mu|\nabla u_{in}|^2)d\Omega + \int_{\Omega_{out(X_{pca},X_T)}} (|I-u_{out}|^2 + \mu|\nabla u_{iout}|^2)d\Omega \quad (7)$$

where C is the active contour, $\hat{\varphi}$ is the shape function of the object of interest given by the PCA ,$\mathbf{x}_{pca}$ is the vector of PCA eigen coefficients, $h_{\mathbf{x}T}$ is an element of a group of geometric transformations parameterized by $\mathbf{x}_T$ (the vector of parameters), g is an edge detecting function Ω_{in} and Ω_{out} are the inside and outside regions of the zero level set of $\hat{\varphi}$, u_{in} and u_{out} are smooth approximations of the original image I in Ω_{in} and Ω_{out} and β_b, β_s , β_r are arbitrary positive constants that balance the contributions of the boundary, shape and region terms .We chose β_b, β_s , β_r , 1, 1/3 and 10 respectively.

3.1 Training Data for Computing PCA

The above method needs some initial training data for calculating PCA eigen coefficients. Because of explicit algebraic form we use ellipse model for generating this training data based on region that segmented from past stage. We calculate statistical properties of the region: center, major axis, minor axis and orientation. Then we generate ellipses based on these parameters and some variations of them for calculating PCA. Figure.2 shows generated training data for segmented region.

We applied this method to refine segmented region and consider active contour as a segmentation result. Figure.3 shows the results.

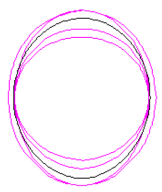

Figure 2: Training data generated from ellipse model of segmented region.

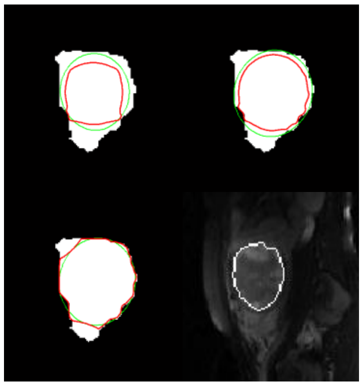

Figure 3: Refined segmented region based on Bresson et al, method and ellipses model; green contours denotes shape model and red contours denote active contour.

4 RESULTS

We have used the above mentioned method on the dataset containing the MR images of 5 patients that were acquired at the Imam Khomeini hospital Medical Imaging Centre. All the patients were imaged on a 1.5T MR scanner used standard clinical imaging protocol to obtain T2-weighted. Each MR image has an in-plan resolution of 512×512 and slice thickness of 5 mm with 15-20 slices.

Fig. 4 shows the segmentation results. With manual initial region selection on first slice, other slices were automatically segmented. The curves are able to converge on the desired boundaries even though some parts of the boundaries are too blurred or missed to be detected by only gray level information. To validate the segmentation results, we compare obtained results with manual segmentation performed by a senior radiologist. We used four measures to evaluate the results which are (M denotes the manually segmented area and an automated segmented area):

• Similarity index: $$S_i = \frac{2N_{T_p}}{N_M + N_A} * 100\%$$

Where N_{T_p} the number of true positive voxels and N_M is the cardinality of M and N_A is the cardinality of A;

• Jaccard index: $$J_i = \frac{N_{T_p}}{N_M + N_A + N_{T_p}} * 100\%$$

• Hausdorff distance between *A* and *M*, defined as *HD* = max (*h* (*M*, *A*), *h* (*A*, *M*)) where *h* (*M*, *A*) = max*m*∈*M* min*a*∈*A* *d* (*m*, *a*), and *d* (*m*, *a*) denotes the Euclidean distance between *m* and *a* (*m* and *a* are points of *M* and *A*, respectively).

•Average distance (*MD)* between the surfaces of *M* and *A*.

As seen in Table 1 similarity index varies from 87.26% to 90.1% with a mean of 87.70%. The Jaccard index varies from 74.65% to 82.62% with a mean of 76.62% which shows a good accuracy of segmentation. The average of Hausdorff distance is 3.42mm that smaller than a voxel size, and constitutes good result. The mean value of the average distance is 0.35mm that represented accuracy of segmentation. Segmentation of fibroids that have calcified and infarcted regions is a challenging task due to global nonhomogenities. Two published papers in uterine fibroid segmentation used level set and active contour methods. These methods are gradient based and are not able to segment these types of tumors. Thus, they only can be useful for complete infarcted fibroids with clear boundaries. We have tried to overcome these limitations by introducing a new method that allows segmentation of these tumors by region based method as initial segmentation. Then, we applied combination of level set based and prior shape model as final segmentation.

Table 1: Evaluation of the segmentation results of images for which a manual segmentation was available.

Patient	Volume		Distance	
	SI	JI	HD	MD
1	88.29	79.76	2.92	0.27
2	88.1	78.9	3.18	0.21
3	90.1	82.62	3.76	0.32
4	87.26	77.55	3.03	0.29
5	84.79	74.65	4.3	0.65
Average	87.70	78.62	3.42	0.35

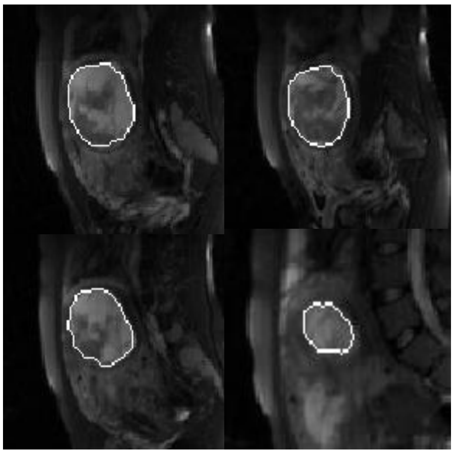

Figure 4: segmentation result using proposed method for some slices of a patient.

5 CONCLUSIONS

This paper proposed an automatic method for the segmentation of uterine fibroid in MR images. Using Chan-Vese method initial segmentation obtained. In second step segmentation refined by applying prior shape model based on Bresson et al, method and ellipses model. The quantitative results illustrate the good performance of this method according to nonhomogeneity region and missing boundary in these types of fibroids. By uterine fibroid segmentation in the future works we can analyze fibroid properties like infarcted or calcified percent region. This task has essential features in diagnosis and treatment of uterine fibroids.

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