Automatic Prostate Segmentation Using Fused Ultrasound B-Mode and Elastography Images

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Abstract. In this paper we propose a fully automatic 2D prostate segmentation algorithm using fused ultrasound (US) and elastography images. We show that the addition of information from mechanical tissue properties acquired from elastography to acoustic information from B-mode ultrasound, can improve segmentation results. Gray level edge similarity and edge continuity in both US and elastography images deform an Active Shape Model. Comparison of automatic and manual contours on 107 transverse images of the prostate show a mean absolute error of 2.6 ± 0.9 mm and a running time of 17.9 ± 12.2 s. These results show that the combination of the high contrast elastography images with the more detailed but low contrast US images can lead to very promising results for developing an automatic 3D segmentation algorithm.

1 Introduction

Low dose rate (LDR) prostate brachytherapy is a common method for treating patients with low risk prostate cancer. In this treatment, 40-100 small radioactive seeds are permanently inserted in the prostate and its periphery. Treatment planning and delivery relies on transrectal ultrasound (TRUS) imaging. In order to create the treatment plan, a pre-operative volume study is carried out in which a set of transverse ultrasound images are collected. These images are then manually segmented to extract the prostate boundaries. A plan is devised to deliver sufficiently high radiation dose to the cancerous tissue while maintaining a tolerable dose to healthy tissue. Reliable segmentation and visualization of the prostate is a vital step in dose planning. Manual segmentation is time consuming and, due to the low signal to noise ratio of ultrasound images, inter and intra-observer variabilities are high. Even though various 2D prostate segmentation methods and some 3D methods have been proposed in the literature [1,2,3,4,5], the effective automatic segmentation of ultrasound images of the prostate has remaining challenges such as user initialization and limited accuracy.

In this paper, we propose a prostate segmentation method based on intra-modality fusion of ultrasound B-mode and elastography. Elastography [6], in

which mechanical properties of tissue are characterized, has shown to be promising in improving the visibility of the prostate gland [7,8]. In a recent study, we have shown that ultrasound dynamic elastography images of the prostate have superior object-background contrast compared to B-mode ultrasound, especially at the base and apex [9]. This is due to the fact that prostate tissue is generally stiffer than the surrounding tissue. We utilize this advantage and combine elastography and US image data for 2D segmentation of the prostate. The elastography images are acquired using a system described in [9] which enables the simultaneous registered acquisition of B-mode and elastography images, thereby eliminating the concerns about image registration and cost.

We use an Active Shape Model (ASM) [10] approach which starts with an initial shape extracted from a large number of elastography and B-mode prostate images. The deformation of this initial shape is restricted to conform to the statistical model and is guided by edge detection from both elastography and B-mode images based on edge gradient similarity and continuity. The use of a statistically created model ensures the compliance of the resulting contours with the overall shape of the organ. Additionally, the restricted deformation results in robustness to poor image quality. The use of a measure of edge continuity [9] in addition to gradient similarity, reduces the effects of strong speckle-induced local edges on the algorithm which improves the rate of convergence. We provide a statistical analysis of the accuracy of our 2D image segmentation method and show that the combined use of elastography and B-mode images improves the accuracy and the convergence rate. Further, we describe a preliminary framework for extending the proposed method to an automatic 3D segmentation algorithm and present an example.

2 Methods

The US and elastography images used in this paper were acquired from patients going through the standard LDR prostate brachytherapy procedure at Vancouver Cancer Center, BC Cancer Agency. Intra-operatively, prior to the procedure, RF data and US images were simultaneously collected using the system described in [9]. In this system RF data is collected at approximately 40 fps from the sagittal array of a vibrating (amplitude 0.5-2 mm, frequency range 2-10 Hz) and rotating (-45° to 50°) TRUS probe (dual-plane linear/microconvex broadband 5 - 9 MHz endorectal transducer, Ultrasonix Medical Corp.). The RF data were processed [11] to obtain sagittal elastography strain images from which conventional transverse images of the prostate were achieved.

Our 2D segmentation approach combines the information from elastography and US images within an Active Shape Model (ASM) which deforms based on gray level similarity and edge continuity. We follow the approach from [10]. First, we construct a training set by manually selecting 30 specific points on the prostate boundary in $N = 25$ mid-gland images from 7 patients. The set of images used for creating the training set does not include the images to be segmented. The manually segmented contours are aligned by using least-squares-based iterative scaling, rotation and translation and the average of the resulting

contours, $\bar{x}$, is used as the initial contour. Then, in order to capture the statistics of the training set, we calculate the covariance matrix, $S = \sum_{i=1}^N dx_i dx_i^T$, where dx_i in the training phase is the distance between each point on the manual contour and the corresponding point on the mean shape. The modes of variation of the shape are described by the eigenvalues, λ_i , and eigenvectors, p_i , of S , from which the t largest eigenvalues are selected as the most significant modes of variation. We selected t such that for $i = 1, \dots, t$, $\lambda_i / \sum \lambda > 5\%$. A shape instance consistent with the training set can thus be created using Eq.(1):

$$x = \bar{x} + Pb \quad (1)$$

where $P = (p_1 \dots p_t)$ is the matrix of the first t eigenvectors and $b = (b_1 \dots b_t)^T$ is a vector of weights. Hence, in the shape fitting phase, given a shape deformation, dx , the shape parameter adjustments, db , can be calculated using Eq.(2).

$$db = P^T dx \quad (2)$$

To calculate the movement, dx_i , for each model point i , a measure of edge gray level similarity was used in [10]. For each point i of each image j of the training set, a normalized edge derivative profile, g_{ij} normal to the boundary, centered at the model point and of length n_p is extracted. g_{ij} is averaged over all images from which the covariance matrix S_{g_i} is calculated to obtain a statistical description of the gray level appearance for every point. During the shape fitting, at each iteration and for every point, sample edge derivative profiles $h_i(d)$ of distance d ($d = -l, \dots, l$) from the boundary point and length n_p are extracted in a similar manner. The square of the Mahalanobis distance of these profiles from the model profile, g_i , give a measure of edge gray level similarity. For each point, the d resulting in the least Mahalanobis distance suggests the required point movement along a line normal to the boundary. The physical values of l and n_p are set to 8 and 5 mm, respectively.

In our data set, we observed that the gray level edge similarity measure alone, gives many false positives due to ultrasound speckle or sharp edge-like structures since only 1D information (normal to the edge) is being analyzed. Therefore, in our approach, we incorporate our edge continuity measure [9] which measures the continuity of the edge in a direction orthogonal to the edge profile. At a distance d from each point, we compute the average normalized cross-correlation, $c_i(d)$, between the edge intensity profile $e_i(d)$ (obtained similar to g_{ij}), of length n_p , with its two neighboring left and right edge intensity profiles. For a continuous edge (i.e. large similarity between $e_i(d)$ and its left and right neighboring profiles), $c_i(d)$ should have a shape similar to a Gaussian function with a large peak and a small standard deviation. We define the edge continuity measure, $K_i(d) = P_{c_i}^2 / \sigma_i(d)$ in which P_{c_i} characterizes the peak and σ_i is the standard deviation of a Gaussian function fitted to $c_i(d)$. For each point, the d resulting in the maximum continuity measure suggests the required point movement along a line normal to the boundary.

We define u_n to be the vector normal to the boundary at the boundary point, d_{gE} , to be the distance from the boundary point suggested by the gray level

similarity, and d_{KUS} , and d_{KE} to be the distances from the boundary point computed from the edge continuity measures in US and elastography images, respectively. Based on the above equations, at each iteration, k , the following steps are performed to deform the current shape points, $x_{current}$ into the next shape, x_{next} .

1. Find the required shape deformation:

$$dx = x_{next} - x_{current} = d_f u_n$$

$$d_f = \alpha_1 d_{gE} + \alpha_2 d_{KUS} + \alpha_3 d_{KE}$$

2. Calculate the optimum pose parameters: scaling, translation and rotation, corresponding to dx , apply this transformation to obtain $T(x_{current})$. Adjusting the pose is required to align $x_{current}$ to be as close as possible to x_{next} before adjusting the shape [10].
3. Calculate $db = P^T(x_{next} - T(x_{current}))$

$\alpha = [\alpha_1 \ \alpha_2 \ \alpha_3]$ are corresponding weights. Due to the large amount of noise in US images, gray level similarity matching in these images does not improve results but degrades convergence, and therefore, it is not included. Our criteria for convergence is when 94% of the contour points have a dx of less than $n_p/2$. Fig. 1 illustrates how d_{gE} and d_{KE} are obtained in an elastography image.

We will provide a comparison of segmentation results using gray level similarity from elastography images, combined edge continuity and gray level similarity from elastography images and finally edge continuity and gray level similarity from both elastography and US images.

Fig. 1. An illustration of how d_{gE} (top point) and d_{KE} (bottom point) are obtained in an elastography image. The gray level similarity measure is compared to that of the model for each corresponding point. The edge continuity measure is maximized over the line normal to the boundary. For clarity, these measures are shown on two different points, whereas they are calculated for single points.

3 Results

To evaluate our 2D segmentation results we measure the mean absolute distance (MAD) and maximum distance (MaxD) between 2D automatic and manual contours. Table 1 provides the mean and standard deviations of MAD and MaxD between 107 manual and automatic contours selected from 7 patients. The results are presented separately for elastography gray level similarity only ($\alpha_a=[1 \ 0 \ 0]$), elastography gray level similarity and edge continuity ($\alpha_b=[0.5 \ 0 \ 0.5]$), and elastography gray level similarity and edge continuity plus US edge continuity ($\alpha_c=[0.5 \ 0.25 \ 0.25]$). Fig. 2 shows an example of segmentation results for the three sets of weight parameters.

The most accurate segmentation results were acquired when $\alpha_c=[0.5 \ 0.25 \ 0.25]$. By using this selection of weight parameters, deformation is mainly guided by the coarser elastography images but also refined by the finer US images. It is specifically seen in the posterior region of the prostate, where elastography image quality is low, that the addition of edge continuity in US images improves segmentation results. This can be observed in Fig. 2. The choice of α_c also results in the convergence of the algorithm in an average of 22 iterations vs. 37 and 98 iterations for α_b and α_a . The maximum number of iterations was set to 50 for α_b and α_c and 100 for α_a . In the case of α_a , 95% of the cases did not converge within 100 iterations.

Fig. 2. 2D automatic segmentation results using elastography gray level similarity (yellow dashed line), elastography edge continuity and gray level similarity (blue line), and elastography gray level similarity and edge continuity plus US edge continuity (red line) on US (left) and elastography (right) images. The manual contour is shown as a blue/white dotted line.

4 Discussion

By visual inspection of the automatic segmentation results, we observed that most of the 2D segmentation error of the mid-gland slice was in the anterior and posterior regions. In elastography images, the blood vessels which lie on the anterior of the prostate appear as stiff tissue and are not always distinguishable

Table 1. Comparison of 2D manual and automatic segmentation showing the Mean Absolute distance (MAD) and Maximum Distance (MaxD - positive sign meaning larger automatic contour) between manual and automatic prostate contours, the number of iterations and duration of the algorithm. K : edge continuity measure, d_g : gray level similarity measure.

	d_g in elast.	d_g and K in elast.	d_g and K in elast. and K in US
MAD (mm)	3.4 ± 1.8	3.4 ± 1.7	2.6 ± 0.9
MaxD (mm)	1.0 ± 9.8	-6.5 ± 7.0	-4.9 ± 4.7
no. of iter.	98 ± 13	37 ± 17	22 ± 15
duration (s)	10.7 ± 1.4	17.3 ± 0.8	17.9 ± 12.2

from the prostate itself. In such cases, the automatic contour extends beyond the actual boundary. In the posterior, due to the relatively low contrast in this region, the automatic contour converges to the darker tissue inside the prostate. By including edge continuity data from US images this problem has been partially resolved. We attribute this low contrast to mainly the slippage between the protective sheath on the probe and the surface of the rectum during elastography data collection. By replacing the 1D axial strain computation with 2D axial/lateral and by increasing the resolution of elastography imaging such problems can be subsided.

Our current elastography data acquisition system has the benefit of collecting inherently registered elastography and US data. Currently the TRUS rotation range is within $\pm 50^\circ$ which may result in missing data in the mid-lateral regions of large prostates. Also, the quality of the B-mode US images acquired along with the elastography data is affected by the computational limitations of the real-time data acquisition system and the ultrasound machine. We are currently working on resolving these problems to improve segmentation results.

The proposed 2D prostate segmentation method using fused elastography and US image information can be extended into 3D by modifying the method that we proposed in [12] which was based on fitting an *a priori* shape to a set of parallel transverse ultrasound images. The algorithm was initialized by the user manually selecting some initial boundary points on the mid-slice. These points were used to un-warp and un-taper all images resulting in a set of elliptical prostate shapes. With the aid of the Interacting Multiple Model Probabilistic Data Association (IMMPDA) [13] edge detector and ellipse fitting, a tapered ellipsoid was fitted to all contours which was then sliced at image depths. The resulting 2D contours were reversely tapered and warped to match the initial images. We showed [12] that the method is fast, and produces smooth contours that are in agreement with the brachytherapy requirements. However, the need for manual initialization limits its use for real-time applications and makes it user dependent. Also, the poor visibility of the boundary at the base and apex complicates segmentation of these regions.

Fig. 3. An example of 3D surface of the prostate created manually (red) and by the automatic algorithm (blue)

To resolve these issues we replace the manual initialization of the 3D semi-automatic segmentation with the described 2D segmentation. Additionally, we employ elastography along with US images for propagating the mid-gland segmentation to the rest of the images. This is done by including an additional IMMPDA edge detection on the coarser elastography images to guide the edge detection on the finer US images. The described framework for automatic 3D prostate segmentation was applied to one patient data set. Fig. 3 shows 3D surfaces created from automatic (blue) and manual (red) segmentation of the prostate for this patient. 11 images were used to construct this surface model. The volume of the manually created surface is 33.9 ml, the volume of the automatically created surface is 34.4 ml, and the volume of the non-overlapping region between the two surfaces is 4.9 ml. A thorough clinical study is required to evaluate this 3D segmentation framework.

5 Conclusions

In this paper we outlined a novel 2D method of prostate segmentation that combines ultrasound elastography imaging with B-mode data. This is the first instance of using such a combination for prostate segmentation and reinforces efforts to improve US segmentation outcomes using elastography data [14]. With the fusion of information from elastic properties of tissue provided by elastography with the acoustic properties of tissue provided by B-mode we developed an automatic and accurate segmentation of the prostate which gives good results in 2D. The automatically generated 2D contours can be used to initialize the mid-slice for 3D segmentation and remove user variability. Additionally, the method can be utilized to register pre and intra-operative prostate images and has the potential of improving intra-operative dosimetry.

Acknowledgments. This project was funded by NSERC Canada (Discovery Grant and Postdoctoral Fellowship). Data collection was funded by NIH grant R21 CA120232-01.

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