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An Elliptical Level Set Method for Automatic TRUS Prostate Image Segmentation

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Abstract- *One of the most important tasks in prostate cancer diagnosis and treatment is segmentation of Transrectal Ultrasound (TRUS) prostate images. Due to the large volumes of TRUS prostate images, automatic segmentation systems are mandatory. Weak prostate boundaries, speckle noise and the short range of gray levels make the task more challenging and difficult. Deformable models have been considered as an effective approach for semi-automatic prostate segmentation. However the main problem toward a fully automatic segmentation system using deformable models is initialization of seed or control points. In this paper an automatic level set prostate segmentation is presented. A classification method is employed to locate the approximate location of the prostate which is used to initiate the proposed elliptical level set contour. The deformations of the level set are guided by a velocity function which is derived using the TRUS prostate image histogram.*

Keywords- *Automatic Image Segmentation, Deformable Models, Level Sets, Ultrasound Imaging, TRUS Prostate Image, Classification, Image Morphology, Thresholding, Speckle Noise.*

1. INTRODUCTION

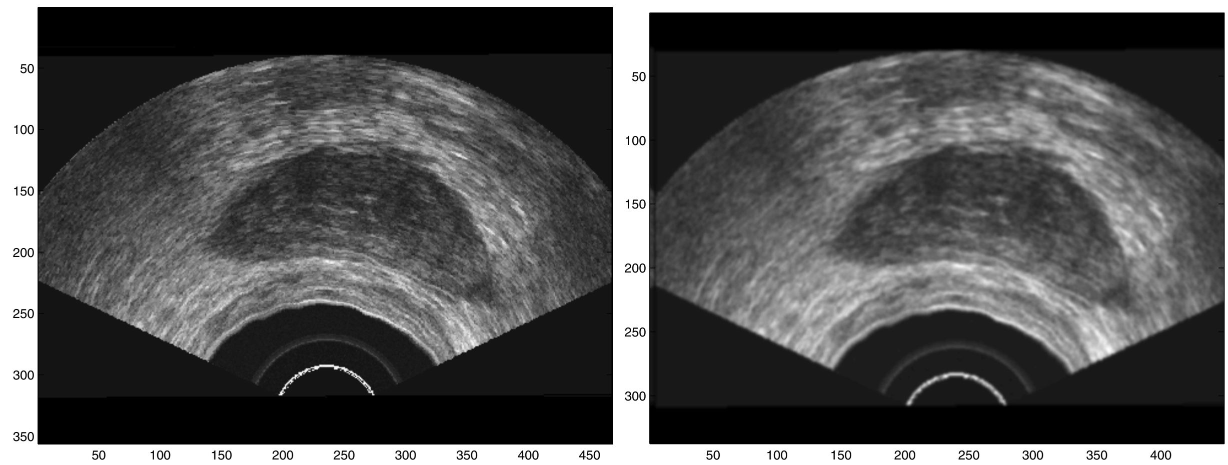
Prostate cancer as the most diagnosed cancer is the second leading cause of cancer death in North America [1] so it is crucial to diagnose the cancer in its early stages. TRUS images are widely used for disgnosis of prostate cancer since they are captured easier and with lower cost in comparison with the other modalities such as MRI and CT. TRUS images are taken in real-time so that not only they are used as complimentary modality to CT and MRI images for diagnosis but they are crucial for cancer treatment planing, needle biopsy and brachytherapy. Diagnosis of the prostate cancer in the early stages increases the chance of successful treatment, however diagnosis in the later stages could also be successfully cured using different treatment planing. As a result it is very important to diagnose the stage of prostate cancer to choose the right treatment planing. Precise information about the size and the shape of prostate play a key role to diagnose the cancer stage. These information usually are extracted from TRUS images by prostate segmentation. However the traditional method of TRUS prostate image segmentation by experts to infer these information manually is tedious, expensive, time consuming and subjective that automated methods of prostate segmentation in TRUS images are in high demand, especially given the increasing amount of TRUS images being collected.

A wide variety of semi-automatic and automatic methods have been proposed to segment prostate in TRUS images. Among different approaches deformable models have been extensively considered for TRUS prostate image segmentation [2, 3, 4, 5, 6] and have outperformed traditional prostate region and boundary segmentation techniques [7, 8, 9].

The main shortcoming of deformable models is manual initialization of the seed or control points which demands for human intervention. In this paper to overcome this problem an automatic contour initialization method is presented. Then the initialized elliptical contour deforms toward the prostate boundaries guided by a velocity function which in turn is derived using TRUS prostate image histogram.

2. LEVEL SETS

Considerable research has been conducted to apply deformable models to medical images [10, 11]. Osher, Sethien and Malladi [12, 13, 14] introduced Level Sets for the first time for shape recovery, however this framework supports a broad range of problems from fluid mechanics to image processing [12]. There are a variety of image processing applications which can be set up in level set framework including segmentation, denoising, and restoration. The zero level set of a higher-dimensional surface can be considered as the initial position of a deforming contour. Therefore in comparison with the other deformable models such as snake, level sets are topological independent and numerically stable to handle singularities.



(a) (b)

Fig. 1. TRUS prostate image (a) Original. (b) After applying a low pass Gaussian filter.

Assume $\wp(t)$ is a simple time dependent closed curve which is considered as the zero level set of a higher dimensional function $\Phi(x, y, t)$ [12, 13, 14]:

$$\wp(t) = \{(x, y)|\Phi(x, y, t) = 0\} \tag{1}$$

To initialize the interface, let the level set function $\Phi(x, y, t)$ be consider as a signed distance function:

$$\Phi(x, y, t) = z(x, y) \tag{2}$$

where $z(x, y)$ is the distance from the closest point on the interface $\wp(t)$ to the point (x, y) such that if the point is inside the interface the distance is negative, for the points outside the curve, the distance z is positive and it is equal to zero for all the points lie on the interface:

$$\wp(t) = \{(x, y)|z(x, y) = 0\} \tag{3}$$

Having $\Phi(x, y, t) = 0$, for each point on the interface, the chain rule can be used to derive

$$\Phi_t + F|\nabla\Phi| = 0 \tag{4}$$

where F and N are velocity function and outward normal respectively so that

$$(x, y)' = F\hat{N},\ \hat{N} = \frac{\nabla\Phi}{|\nabla\Phi|} \tag{5}$$

3. THE PROPOSED METHOD

We are interested in deformable approach for medical and biomedical image segmentation. In our previous work [15] we developed an adaptive level set method for Neuron Stem Cell (NSC) segmentation in which the velocity function F was set up based on the gradient of a narrow-band zero level set. Due to presence of several spurious edges and speckle noise in TRUS prostate images, gradient-based velocity functions are inappropriate to be employed as deforming engine of the level set. In turn the gradient-based automatic contour initialization which is discussed in [15] cannot be applied here.

To initialize the level set contour for TRUS prostate images in the proposed method, we first pre-segment the TRUS image to find the approximate prostate region which is later used to initiate an elliptical level set for fine prostate segmentation.

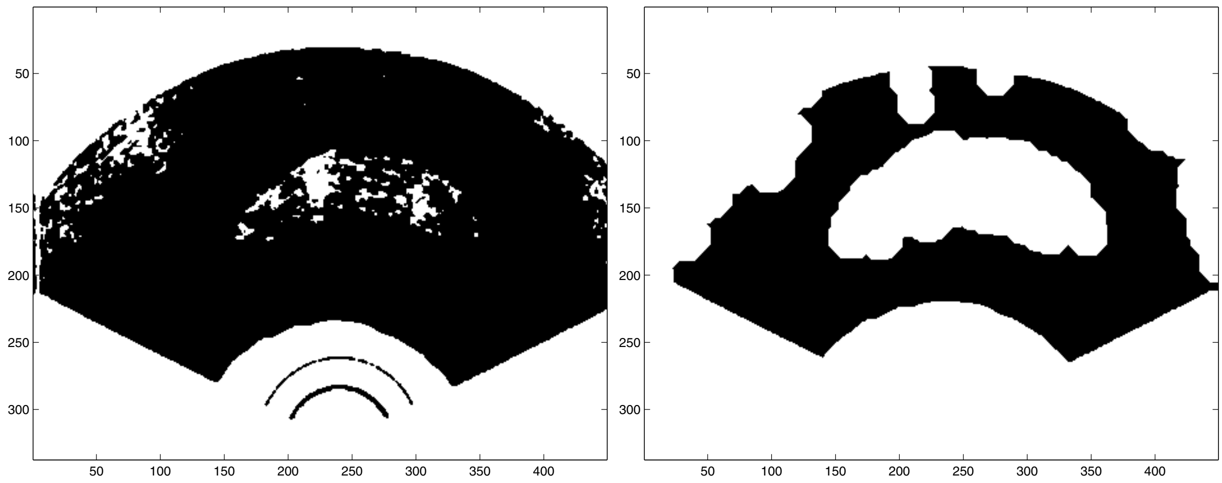
3.1. Pre-Segmentation

At first to eliminate the noise and smooth out the background and prostate regions a Gaussian low pass filter is applied to the TRUS image. Assume σ^2_{pst} and σ^2_{bkg} be prostate region variance and background variance respectively. To discriminate prostate pixels from the background, the low pass filtered TRUS image is thresholded with threshold T. The threshold T is selected by minimizing the inter-class variance

$$\sigma^2(T) = n_{pst}(T) \cdot \sigma^2_{pst}(T) + n_{bkg}(T) \cdot \sigma^2_{bkg}(T) \tag{6}$$

where $n_{bkg}(T)$ and $n_{pst}(T)$ are the number of pixels in the background and the prostate regions respectively and $\sigma^2(T)$ is inter - class variance considering the threshold (T).

Image Morphology. In the next step morphology operators are applied to generate a closed and smooth prostate region. A circular disk is employed as the morphology mask and dilated over the classified TRUS prostate image



(a) (b)

Fig. 2. (a) Classification by minimizing the inter-class variance. (b) Applying the morphological operators on the classified image for primary segmentation.

so that the preostate area is pre-segmented

$$I \oplus M \equiv \{I_i + M_j : I_i \in I,\, M_j \in M\} = \bigcup_{M_j \in M} I_{+M_j} \quad (7)$$

where I and M are TRUS prostate image and the mask (disk) respectively and

$$I_{+M_j} \equiv \{I_i + M_j :\, I_i \in I\} \quad (8)$$

is translation of I along the M_j.

3.2. *Elliptical Level Set*

We consider an elliptical contour as the zero level set of a $3-D$ hyper ellipse

$$\frac{(x-x_c)^2}{d_a^2} - \frac{(y-y_c)^2}{d_b^2} = 1 \quad (9)$$

where (x_c, y_c) are the ellipse center coordinates, d_a and d_b are the ellipse vertical and horizontal axis. The centroid of pre-segmented TRUS prostate image is considered as the center of the ellipse and it is initialized so that it is completely located inside the pre-segmented prostate area as depicted in Fig. 3(a).

Having the contour initialized, to find a solution for (4), an appropriate velocity function F must be designed. We wish the interface evolves toward the prostate boundaries and converges in its vicinity. The velocity function F must be designed based on the specific features of the tissue or object such as edges, texture, gray level intensities and shape. Due to the speckle noise residuals, there are several spurious edges in TRUS prostate images so that gradient-based velocity functions are inappropriate. Texture information can be used to define the velocity function to segment the prostate boundary. We considered a bank of 16 Gabor filters including four orientations and four radial frequencies to derive the velocity function, however the prostate texture features are very weak. To achieve valuable texture features a larger Gabor filter bank must be considered and the computational burden does not seem to be reasonable for the real-time applications.

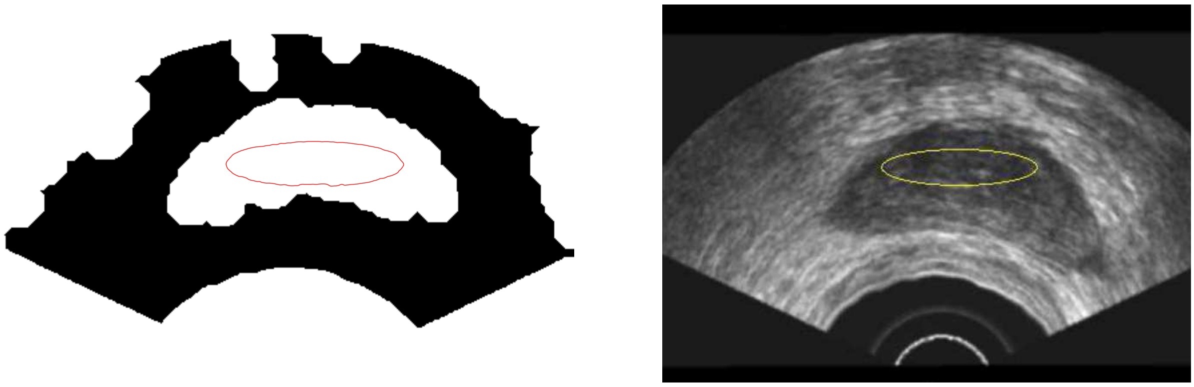
Based on the TRUS prostate images, we designed and tested different velocity functions. The proposed velocity function uses the first and the second order statistics of the TRUS image gray level intensities which produces the best results according to the segmentation accuracy and the time spent:

$$F = -exp\{\epsilon\aleph - \beta \times \frac{(I-\mu)^2}{\sigma^2}\} \quad (10)$$

where $epsilon$ and β are constants, I is denoised TRUS prostate image, μ and σ are the first and second moments which are illustrated from the TRUS image and $\aleph$ is the contour curvature

$$\aleph = \nabla . \frac{\nabla\Phi}{|\nabla\Phi|} = \left\{ \frac{\Phi_{xx}\Phi_y^2 - 2\Phi_x\Phi_y\Phi_{xy} + \Phi_{yy}\Phi_x^2}{(\Phi_x^2 + \Phi_y^2)^{\frac{3}{2}}} \right\} \quad (11)$$

As it can be observed in Fig. 4 we fit a Guassian to the denoised TRUS image histogram so that μ and σ are the mean and variance of the Gaussian pdf.



(a) (b)

Fig. 3. Initialized elliptical interface (a) Superimposed on pre-segmented image. (b) Superimposed on denoised TRUS prostate image.

4. RESULTS

To derive the results a Gaussian low pass filter is applied to the TRUS prostate images at first. Then the proposed pre-segmentation algorithm classifies the denoised image and smoothen the results by applying mathematical morphology operator. The pre-segmented image is used to locate the approximate prostate region which in turn is used to initialize the elliptical contour. Finally the contour evolves toward the prostate boundary guided by the first and second moments of the Gaussian pdf fitted to the TRUS image histogram.

Figs. 1(a) and (b) show the original and denoised TRUS prostate images respectively. As we can observe not only speckle noise is reduced but the background and prostate regions are smoother and have less intensity variations in the denoised image. The classified and pre-segmented results obtained by minimizing the inter-class variance and dilating a disk mask over the denoised TRUS image are depicted in Figs. 2(a) and 2(b) respectively.

As it can be observed in Fig. 3(a) the elliptical interface is initialized using the pre-segmented TRUS image so that it is completely located inside the pre-segmented prostate area. In Fig. 3(b) the initialized interface is superimposed on denoised prostate image. Fig. 5 shows the initialized contour and its deformations toward the prostate boundary. This image sequence shows the contour after 0, 90, 180, 270, 360 and 450 iterations where the contour stops in the vicinity of prostate boundary.

As can be observed by applying the proposed automatic level set method, it is able to segment the prostate boundary in TRUS images successfully while the human intervention for contour initiation is eliminated.

5. CONCLUSIONS

Measure the size and shape of prostate in large volumes of TRUS prostate images is crucial for prostate cancer diagnosis and treatment planning. This paper presents an automatic segmentation method using level sets for prostate segmentation in TRUS prostate images which is the essential stage in prostate cancer diagnosis. The proposed method is constructed based on the real-time applications and key features of the TRUS prostate images.

At first a course segmentation method is applied to pre-segment the approximate prostate region in TRUS image. Having the approximate location of prostate an elliptical level set will be initialized and deformed toward prostate boundaries. The deformations of the level set are based on a velocity function which is derived using the first and second statistics of TRUS prostate image histogram.

The main focus of this paper is automatic initialization of the interface, however the quality of segmentation has crucial importance. Although it can be seen from the previous section that such a level set approach has produced very promising results, when the signal to noise ratio is very poor due to high speckle noise or the prostate boundary is very weak or partially missed due to shadow areas the proposed method leak to the background and fail to produce a smooth segmentation.

Our future work includes further improving the proposed method to be more robust with speckle noise and to be capable of segmentation in poorer TRUS prostate images with shadow areas and missing boundaries.

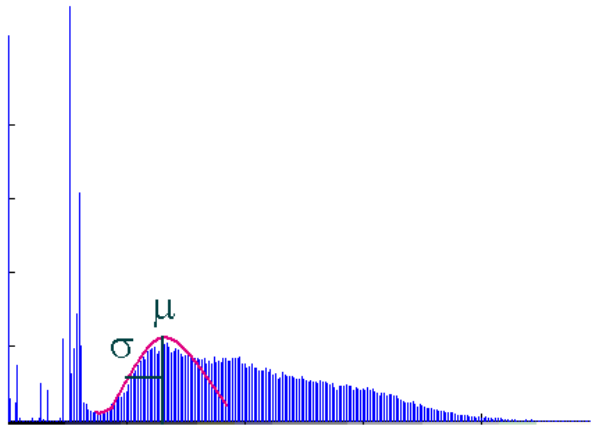


Fig. 4. Denoised TRUS prostate image histogram.

6. ACKNOWLEDGEMENTS

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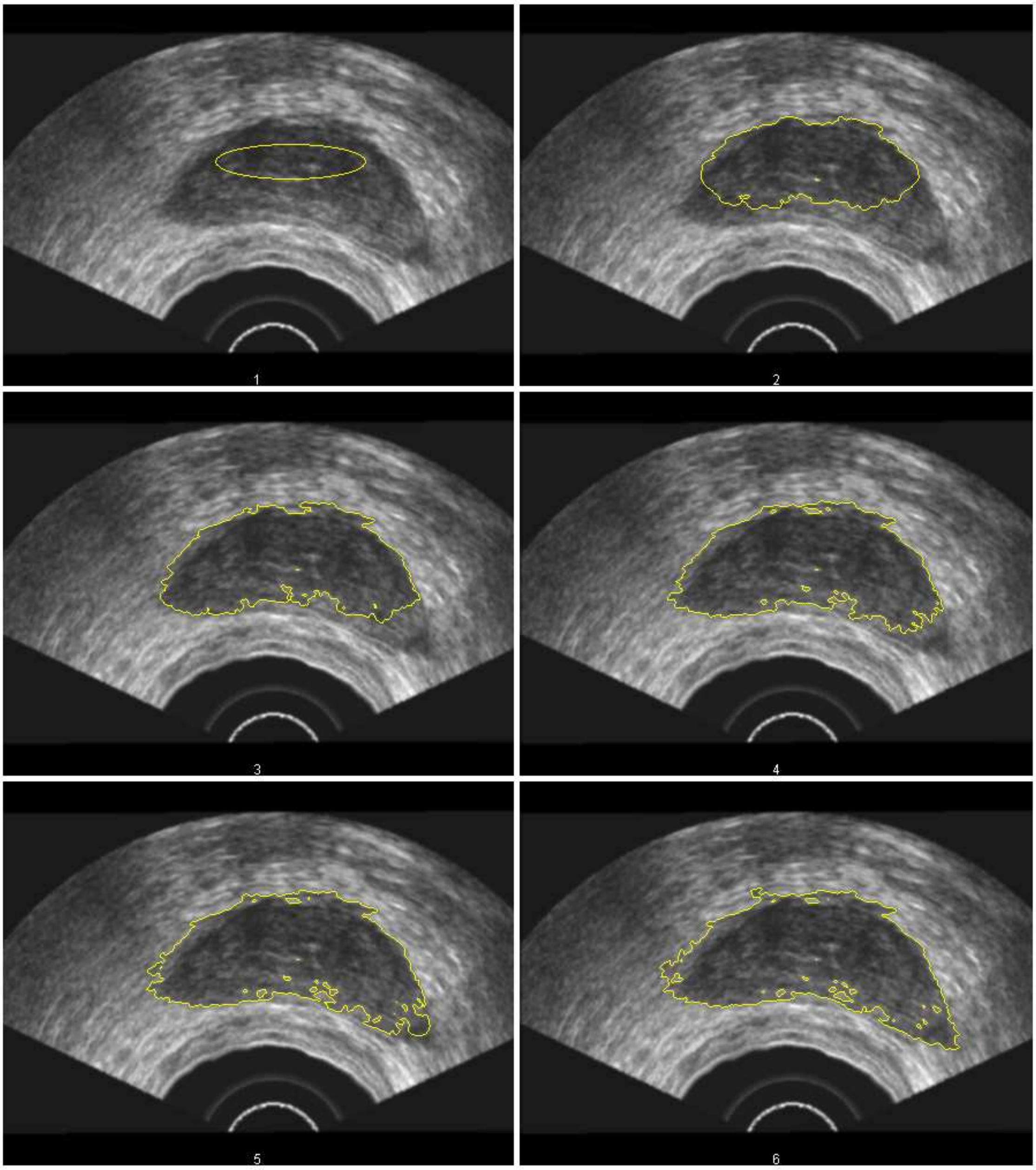

Fig. 5. Deformations of the level set toward prostate boundary in TRUS image after 0, 90, 180, 270, 360 and 450 iterations.