An Approach to Prostate Segmentation on MR Images

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Introduction: Prostate segmentation on MR images attracted greater research interest in recent years, with the introduction of conformal radiotherapy (CRT) and intensity modulated radiotherapy (IMRT) for prostate cancer. Accurate delineation of tumor target volume and organs at risk becomes increasingly important in radiotherapy treatment planning. However, it is difficult to perform fully automated segmentation in T2-weighted images because the signal intensity within the prostate is inhomogeneous as it reflects the underlying characteristics of the glandular tissue [1]. The interface between the prostate and the rectum and bladder is not always clear. Some parts of the boundary defined by the prostatic capsule are less distinct because the fibromuscular band blends with urethral sphincter at the prostate apex and bladder musculature at its base. While contouring manually, oncologists know the pelvic anatomy (not only the shape of prostate, but also its spatial relationship with other organs, such as bladder, rectum, and seminal versicles) and take the intensity distribution not only within but also surrounding the prostate into account. In order to incorporate this *a prior* knowledge of the neighbouring intensity distribution into model based segmentation method, Intensity Distribution Shell (IDS) model was proposed in this study. Given a prostate surface, by dilating and shrinking given numbers of voxels, we get two new surfaces enclosing the neighbouring tissues. The volume between these two surfaces is called a shell. The number of voxels is the shell thickness. The IDS model is the integration of a shape model obtained by principal component analysis (PCA) and an intensity distribution model represented by the histogram of the voxels within a shell with predefined shell thickness enclosing the shape surface.

Methods: MR examinations of 23 patients with prostate cancer were performed on a 1.5-T whole-body MR imaging system (Siemens Sonata). T2-weighted (TR/TE, 3200/133) transverse images of pelvis were obtained with 3 mm slice thickness, 448×291 matrix and a field-of-view of 23×23cm^2. Thirty-five transverse slices were obtained and each slice was saved as an 896×896×16 bit DICOM3 file. Fifteen prostate datasets were used to as training datasets to construct the shape and intensity distribution model, the rest eight datasets were used to test the segmentation method. The prostates were outlined on each axial image by an oncologist. The 2D contours were stacked and converted into a 3D binary image (intensity of voxels of prostate was set as 1 and background 0) with isotropic voxel size 0.5×0.5×0.5*mm* by interpolation, which is considered as the ground truth volume.

To build up the shape model, we followed these steps. From the binary image, prostate surface was extracted by marching cube algorithm. The prostate surface was then sampled nearly uniformly over the unit sphere by using icosahedron subdivisions [2]. Subdivision level was set as 20 and it resulted in 4,002 sampling points. These prostates represented by point clouds was registered using Iterative Closest Point (ICP) algorithm [3]. PCA model was then built on these registered point clouds. Our shape model consists of the 10 most important deformation modes, which can represent 99% variance of the training sets.

The intensity distribution model was established from the histogram within the shell. For each prostate, the binary image with isotropic voxel size obtained previously was dilated by *m* voxel and shrunk by *n* voxel to obtain the outer and inner surface of the shell, respectively. The shell thickness thus was *m*×*n*×0.5*mm*. The sub-shell formed by the outer surface and the prostate surface was called outer shell, while that by the inner surface and the prostate was called inner shell. The histograms of voxels within the inner and outer shells were computed, respectively. Each histogram has 100 bins. When the histograms were obtained from all the 15 training sets, two PCA models were built for the histograms of inner and outer shell, respectively. We used top 10 modes for each PCA model, which covered 95% variance of the training histograms.

This intensity distribution shell model is the joint model by appending the two intensity distribution PCA models to the shape PCA model. It contains not only the shape knowledge from the expert, but also the appearance knowledge of the prostate (the intensity distribution of inner shell) and the intensity distribution knowledge of the surrounding tissues (the PCA model of the outer shell). The segmentation was then carried out by finding the parameters in the joint PCA model yielding the best match of shape and intensity distributions. The fitness function for shape matching was based on energy [4], and that for intensity distribution matching was the distance function based on cumulative distribution functions [5]. Weighting factors can be assigned to the three fitness functions to emphasize the contribution of each PCA model.

Results: The segmented prostates were visually checked and improvement was seen at the prostate apex and base portion. For quantitative evaluation, the segmented prostate volume (SV) and ground truth prostate volume (GV) were compared with each other. The volume change (volume of SV minus volume of GV), the centroid displacement (centroids of SV minus centroids of GV), the probability of detection (volume of SV inside GV divided by volume of GV), the probability false alarm (volume of SV inside GV divided by volume of GV) were calculated and tabulated in Table 1. The mean (±standard deviation) of volume change is 2.1±3.1 cm^3, which means that generally the algorithm overestimated the volume of prostate. However, the error is less than 10% of the prostate volume. The centroids displacement is of important to oncologist in treatment planning. The average displacement is 5.1±5.3 *mm*. The probabilities of detection (82.6%±5.1%) and false alarm (10%±3.8%) are comparable to those reported in literature.

Table 1. The quantitative evaluation of the IDS model based segmentation

Patient ID	Volume change (cm^3)	Centroid displacement (*mm*)	Probability of detection (%)	Probability of false alarm (%)
01	1.24	3.5	88.4	10.6
02	5.34	10.2	75.6	14.8
03	-3.60	1.3	78.3	15.3
04	4.28	0.9	82.5	9.6
05	-2.19	2.8	81.7	6.8
06	3.13	3.2	84.6	5.9
07	8.11	15.9	79.2	14.3
08	0.25	2.7	90.8	7.8

Discussion: Most of the model based segmentation methods utilise experts' knowledge of the shape of interest only [4]. These pure geometrical shape models lack of intensity information, which could be important to subsequent segmentation. Shape-appearance model was therefore proposed to consider the intensity distribution within the prostate (the appearance) in dealing with segmentation on CT images [5]. In MR images, the intensity information in the area surrounding the prostate is also used by oncologist when doing manual delineation, especially for the prostate apex and base portion. With the proposed intensity distribution shell model, the intensity information of both the interior and exterior of the prostate can be taken into account by specifying the shell thicknesses. The segmentation results were visually validated and quantitatively evaluated. One of the possible improvements is using varying shell thicknesses instead of constant thickness in this preliminary study. For example, the shell thickness at the portion with clear boundary could be set to 0 to exclude the effect of surrounding tissues on the intensity distribution shell. These portions generally appear at the middle slices in inferosuperior direction, in which the prostate boundary is relatively distinct. Further studies should include more datasets and try to reduce computational time. The organ at risks, such as bladder and rectum are of interest as well.

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