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# A supervised learning framework of statistical shape and probability priors for automatic prostate segmentation in ultrasound images

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ABSTRACT

Prostate segmentation aids in prostate volume estimation, multi-modal image registration, and to create patient specific anatomical models for surgical planning and image guided biopsies. However, manual segmentation is time consuming and suffers from inter-and intra-observer variabilities. Low contrast images of trans rectal ultrasound and presence of imaging artifacts like speckle, micro-calcifications, and shadow regions hinder computer aided automatic or semi-automatic prostate segmentation. In this paper, we propose a prostate segmentation approach based on building multiple mean parametric models derived from principal component analysis of shape and posterior probabilities in a multi-resolution framework. The model parameters are then modified with the prior knowledge of the optimization space to achieve optimal prostate segmentation. In contrast to traditional statistical models of shape and intensity priors, we use posterior probabilities of the prostate region determined from random forest classification to build our appearance model, initialize and propagate our model. Furthermore, multiple mean models derived from spectral clustering of combined shape and appearance parameters are applied in parallel to improve segmentation accuracies. The proposed method achieves mean Dice similarity coefficient value of 0.91 ± 0.09 for 126 images containing 40 images from the apex, 40 images from the base and 46 images from central regions in a leave-one-patient-out validation framework. The mean segmentation time of the procedure is 0.67 ± 0.02 s.



## 1. Introduction

Prostate adenocarcinoma is a major health problem and accounted for over 70,000 deaths in European Union in 2008. Worldwide, around 899,000 people were detected with prostate cancer in 2008 and it accounted for over 258,000 deaths (Ferlay et al., 2010). Trans rectal ultrasound (TRUS) guided prostate biopsies performed without the knowledge of cancer location in the prostate often suffer from sampling errors. Approximately 30% of these biopsies miss prostate cancer and often targeted re-biopsies result in detection of cancer in 40% of the cases (Jemal et al., 2010). Accurate prostate segmentation in TRUS may aid in biopsy needle placement and multi-modal image fusion between TRUS and magnetic resonance imaging (MRI) to improve malignant tissue sampling during biopsy, as stated in Yan et al. (2010). Prostate volume determined from segmented TRUS images serves as an important parameter in determining the presence of benign or malignant tumors during diagnosis and treatment of prostate diseases. Often, prostate area and height in 2D axial mid-gland TRUS slices are used in planimetry calculation, prolate ellipse volume calculation, and in ellipsoid volume measurement technique to determine the prostate volume. In prostate brachytherapy, oncologists prepare a set of manually segmented parallel TRUS images to obtain the prostate volume to plan the placement of the seeds. Hence, fast semi-automatic or automatic prostate segmentation in 2D slices or 3D volume is often useful in diagnostic or treatment procedures. However, accurate computer aided prostate segmentation from TRUS images is a challenging task due to the low contrast of TRUS images, speckle, and shadow artifacts. Heterogeneous intensity distribution inside the prostate gland and surrounding tissues further hinder the development of a global segmentation model based on intensities. The primary prostate segmentation challenges in TRUS images are illustrated in Fig. 1.

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Added to these challenges the prostate shape and size may vary significantly. In Fig. 2 we observe how prostate shape and size vary across different datasets, while Fig. 3 illustrates an example of contrast variations with different machine manufacturers. Finally, Fig. 4 shows the change in image contrast depending on the acquisition parameters. Prostate shape and intensity prior models are often used for prostate segmentation in ultrasound images. However, large variations in shape and intensity spaces adversely affect the segmentation accuracies of these models.

## 2. Previous work and motivation

In the last decade, several segmentation methods have been developed for segmentation of the prostate in TRUS, MRI and computed tomography (CT) images, that are the three primary imaging modalities that aid prostate cancer diagnosis and treatment. Broadly, these methods could be categorized into contour and shape based methods, region based methods, supervised and un-supervised classification methods, and hybrid methods depending upon the information used and the theoretical approach adopted (Ghose et al., 2012b).

Contour and shape based methods use prostate boundary/edge information to segment the prostate. Since, edge information is often unreliable in TRUS and CT images, and in the base and the apex regions of the MR images prior shape information is incorporated to provide better results (Ghanei et al., 2001; Shen et al., 2003; Zhu et al., 2007; Mahdavi et al., 2011). Ghanei et al. (2001) used a shape-constrained deformable mesh in a multi-resolution framework to achieve 3D segmentation of the prostate. Cootes et al. (1994) proposed to segment the prostate in MR slices using the framework of active shape model (ASM) i.e. they proposed prostate segmentation as one of the applications of their generic ASM model. Zhu et al. (2007) proposed a hybrid of 2D and 3D ASMs to segment the prostate in sparse MR datasets. Shen et al. (2003) used rotationally invariant Gabor features computed with respect to the TRUS probe in a multi-resolution and multi-orientation ASM framework. The real and imaginary parts of Gabor features were used for smoothing and edge detection, respectively. The ASM was deformed in an hierarchical framework focusing on coarse to fine Gabor features in multi-resolution. In recent years, Mahdavi et al. (2011) used a tapered ellipsoid model to segment the prostate. The authors used untapering and warping of the image to make the shape of the prostate elliptical. After initial fitting, a deformation model was used to get the final fitting of the prostate boundary traced by interacting multiple modes probability density association filter (Abolmaesumi and Sirouspour, 2004).

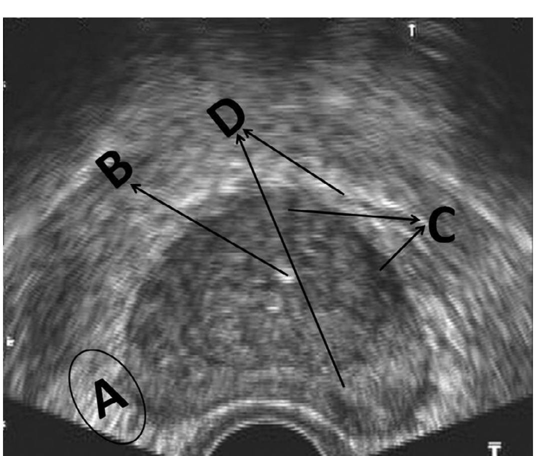


**Fig. 1.** Prostate segmentation challenges, A = low contrast, B = micro calcification, C = intensity heterogeneity inside prostate, D = speckle noise (Yan et al., 2010).

Region based methods use local intensity or statistics like mean and standard deviation in an energy minimization framework to achieve segmentation. The methods in this category primarily vary depending on the energy minimization framework. For example, in atlas-based methods, a model of the prostate is created from manually segmented training images and intensity difference between the model and a new un-segmented image is minimized (Klein et al., 2008; Dowling et al., 2011). In contrast, in region based level sets prior mean and standard deviation information of the prostate region from manually segmented images are used to maximize the distance between prostate and background regions depending on region based statistical moments and propagate an implicitly defined deformable model whose energy is minimized at the zone of convergence of the two regions (Costa et al., 2007; Rousson et al., 2005; Chen et al., 2009).

Supervised and un-supervised classification methods use simple features like intensity or higher dimensional features like filter responses to cluster and/or classify the image into prostate and background regions. The objective of such methods is to group similar objects together based on the feature vectors. Unlike region based methods of energy minimization frameworks, a thresholding scheme is used based on some proximity or distance measure to group similar objects together (Zaim, 2005; Li et al., 2011; Liao and Shen, 2011).

Hybrid methods combine information from contour, shape, region and/or supervised or un-supervised classification information to segment the prostate. These methods are more robust to imaging artifacts and noise (Tutar et al., 2006; Zhan and Shen, 2006; Cosío, 2008; Yan et al., 2010; Makni et al., 2009; Martin et al., 2010; Gao et al., 2010; Toth et al., 2011a; Song et al., 2009; Li et al., 2011; Liao and Shen, 2011; Chen et al., 2011; Toth and Madabhushi, 2012; Chowdhury et al., 2012). For instance, Tutar et al. (2006) used the average of three manually delineated prostate contours to construct a 3D mesh with spherical harmonics to represent the average model of the prostate. The shape model and region-based information were then combined in a Bayesian framework to provide an energy function, which was minimized to achieve segmentation. Zhan and Shen (2003) proposed to model the texture space by classifying into prostate and non-prostate regions by using support vector machines. The texture features were determined by rotationally invariant Gabor filters and the classified feature space was subsequently used as an external force in a deformable model framework to segment the prostate.

Cosío (2008) used Gaussian mixture modeling of prostate location coordinate values and intensities to cluster prostate and non-prostate regions. Finally, a Bayes classifier was used to achieve a binary segmentation. A multi-population genetic algorithm with four pose and ten shape parameters was used to optimize an ASM in a multi-resolution framework to segment the prostate. To reduce the effect of shadow artifacts, Yan et al. (2010) used contrast variations in normal vector profiles to automatically determine salient points and provide prostate boundaries. Prior shape information of the prostate shape aided to determine the missing points in shadow regions in TRUS images. Optimal search performed through vector profiles perpendicular to the salient points was used to determine prostate boundary with a discrete deformable model in a multi-resolution, energy minimization framework. In an approach similar to the method of Cosío (2008), Makni et al. (2009) modeled the intensities of the prostate region as a mixture of Gaussians. They proposed a Bayesian approach where the prior probability labeling of the voxels was achieved by using a shape restricted deformable model and Markov field modeling. The conditional probability was associated with the modeled intensity values, and the segmentation was achieved by estimation of an optimum label for prostate boundary pixels in a MAP decision framework.