Prostate Boundary Detection From Ultrasonographic Images

Fan Shao, PhD, Keck Voon Ling, PhD, Wan Sing Ng, PhD, Ruo Yun Wu, ME

Objective. Prostate diseases are very common in adult and elderly men, and prostate boundary detection from ultrasonographic images plays a key role in prostate disease diagnosis and treatment. However, because of the poor quality of ultrasonographic images, prostate boundary detection still remains a challenging task. Currently, this task is performed manually, which is arduous and heavily user dependent. To improve the efficiency by automating the boundary detection process, numerous methods have been proposed. We present a review of these methods, aiming to find a good solution that could efficiently detect the prostate boundary on ultrasonographic images. Methods. A full description of various methods is beyond the scope of this article; instead, we focus on providing an introduction to the different methods with a discussion of their advantages and disadvantages. Moreover, verification methods for estimating the accuracies of the algorithms reported in the literature are discussed as well. Results. From the investigation, we summarize several key issues that might be confronted and project possible future research. Conclusions. Those model-based methods that minimize user involvement but allow for interactive guidance of experts will likely be most immediately successful. Key words: algorithm verification; boundary detection; prostate; ultrasonographic image.

Abbreviations
DDC, discrete dynamic contour; MRF, Markov random field; RBR, radial bas-relief; 3D, three-dimensional; TRUS, transrectal ultrasonography; 2D, two-dimensional

Prostate diseases are common in adult and elderly men. Benign prostatic hyperplasia (BPH) usually leads to urinary symptoms of varying severity in almost 50% of men older than 60 years. These symptoms have a considerable impact on quality of life and may lead to serious complications such as acute urinary retention. The most serious problem, however, is prostate cancer. It has the second highest mortality rate, after lung cancer, among all cancers in men in North America; it is the sixth most common cancer in men in Singapore. The increase in the reported prevalence of prostate diseases is thought to be due to longer life expectancy, increased prostate disease awareness, prostate-specific antigen screening, and imaging techniques such as transrectal ultrasonography (TRUS).

Ultrasonographic imaging has several favorable properties compared with other medical imaging modalities. It does not require the special equipment that radiographic computed tomography and magnetic resonance imaging require, and portable ultrasonographic imaging...
instruments are available. Unlike other tomo-
graphic techniques, ultrasonography offers
interactive visualization of the underlying
anatomic structures in real time and has the abil-
ity to show dynamic structures within the body.
Needles and catheters can also be deployed
under ultrasonographic guidance. For this rea-
son, TRUS is commonly used for diagnosis of
prostatism, detection and staging of prostate
cancer, and real-time image guidance of mini-
mally invasive therapeutic procedures.5,6

Table 1 lists the major applications in which
prostate boundaries and volumes obtained from
TRUS images play a key role in clinical deci-
sions.7 The gland volume may be derived from
the boundaries by planimetric volumetry.8

However, prostate boundary detection from
ultrasonographic images still remains a challeng-
ing task because of the poor contrast between
the prostate and surrounding tissues, speckle
noise, shadowing, and refraction artifacts.9 For
this reason, manual contouring is currently
the only robust, reliable segmentation procedure
available for TRUS of the prostate. This method
relies on expert observers, such as experienced
surgeons or radiologists, to draw the desired
boundaries directly onto the raw images.

Manual contouring is only suitable for cross-
sectional two-dimensional (2D) images,
because it is too hard to accurately outline the
surface of the prostate from three-dimensional
(3D) volume data displayed in a 2D scene.

Unfortunately, manual contouring is too time-
consuming and arduous. The results are heavily
dependent on the observers' experience and
consequently variable between observers
(interobservability) and even within an observ-
er when performing the same job at different
times (intraobservability).

A possible solution to improve the efficiency is
to automate the boundary detection process
with minimal manual involvement, especially
for robotic (or computer-assisted) surgery.10

Although numerous methods have been pro-
posed to automatically (partially or fully) detect
prostate boundaries from ultrasonographic
images,7,11–27 we are unaware of any surveys on
this particular topic.

This article provides an overview of current
methods used for prostate boundary detection
from ultrasonographic images. A full descrip-
tion of various methods is beyond the scope of
this article, and readers should see the refer-
ences for additional details. Instead, we focus
on providing an introduction to the different
methods and various issues that must be con-
fronted.

This article is organized as follows. In the
first section, we give a review of the methods
that have recently been applied to 2D prostate
boundary detection. Three-dimensional prostate
surface detection approaches are then discussed
in the second section. The third section
describes the evaluation criteria for validating
algorithms. Some key issues relating to the task
of prostate boundary detection are discussed in
the fourth section.

Table 1. Major Applications for Which Prostate Boundaries and Volumes Play Key Roles in Clinical Decisions

<table>
<thead>
<tr>
<th>Application</th>
<th>Parameter of Interest</th>
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<tbody>
<tr>
<td>Diagnosis</td>
<td></td>
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<tr>
<td>Prostate-specific antigen density</td>
<td>Volume</td>
</tr>
<tr>
<td>Assessment of benign prostatic hyperplasia</td>
<td>Volume</td>
</tr>
<tr>
<td>Treatment</td>
<td></td>
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<tr>
<td>Prostate brachytherapy</td>
<td>Boundary</td>
</tr>
<tr>
<td>High-intensity focused ultrasonography</td>
<td>Boundary</td>
</tr>
<tr>
<td>Cryotherapy</td>
<td>Boundary</td>
</tr>
<tr>
<td>Transurethral microwave therapy</td>
<td>Volume</td>
</tr>
<tr>
<td>Resection of benign tissue</td>
<td>Volume</td>
</tr>
<tr>
<td>Follow-up</td>
<td></td>
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<tr>
<td>Hormonal treatment</td>
<td>Volume</td>
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Adapted with permission from Y. Kim, PhD (University of Washington, Seattle, WA).
Two-dimensional Prostate Boundary Detection From Sonographic Images

This section presents a review on several common methods that have appeared in recent literature for 2D prostate boundary detection. According to the image segmentation mechanism applied to these methods, we classify them into 3 categories: edge-based methods, texture-based methods, and model-based methods. Table 2 summarizes algorithms and representative works for prostate boundary detection within these 3 categories.

Edge-Based Detection Methods
The common feature of this class of methods is the use of edge detectors to identify all the edges in the image, followed by edge selection and linking to outline the prostate boundary. Typically, these methods locate edges that correspond to local peaks in the intensity gradient of an image. Such a strategy is very straightforward and works well when the boundary is clearly defined. However, because of the poor quality of ultrasonic images, these methods usually lead to both spurious boundaries in highly textured areas and missed boundaries where the prostate boundary is not well delineated. Therefore, both edge detectors and edge selection and linking algorithms should be well designed to achieve the desired prostate boundaries in ultrasonic images.

In their work, Aarnink et al.11 and Huynen12 introduced a practical method for automated prostate contour detection based on an edge detection preprocessing algorithm (minimum/maximum filtering). In this algorithm, the second derivative in gradient direction is implemented with local minimum and maximum filters, combined with a gray value to assess the local gradient in the direction from the minimum to the maximum. With this algorithm, all edges in the images are detected (Fig. 2h). Then knowledge-based features, such as expected shape (kidney-like) and ultrasonographic appearance of the prostate (looking from within the gland, the edges to be detected are transitions from dark to light), are used to select the correct edges. With adaptive interpolation, the prostate boundary is finally produced. Figure 2 shows an example of the contour detection in an ultrasonographic prostate image.12 A major disadvantage of their method is that artifacts such as cysts, calcification, and shadowing could lead to erroneous edges.

To improve the edge detection and localization, Aarnink et al.13 further introduced a technique of adjusting the edge detection parameter to signal information. First they investigated the influence of parameter settings associated with the filtering (the size of the smoothing filter and the size of minimum/maximum filter). Then the local SD of the gray value is used to identify more or fewer homogeneous regions that are filtered with coarse resolution, whereas areas with greater deviation indicate that gray level transitions occur, which should be preserved with the use of smaller filter sizes to improve edge localization. With the improved result, more interpolation to find a closed contour is needed, and the definition of the prior knowledge becomes more important.

Table 2. Categorization of Methods for 2D Prostate Boundary Detection From Sonographic Images

<table>
<thead>
<tr>
<th>Methods</th>
<th>Representative Works</th>
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<tbody>
<tr>
<td>Edge-based</td>
<td>Second derivative in gradient direction with local minimum/maximum filters11–13</td>
</tr>
<tr>
<td>Minimum/maximum filtering</td>
<td>Match filtering in radial directions14,15</td>
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<tr>
<td>Derivative edge detector</td>
<td>Edge-based technique5</td>
</tr>
<tr>
<td>Weak membrane fitting</td>
<td>RBR and harmonics method16,17</td>
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<tr>
<td>RBR</td>
<td>Pixel classifying based on 4 texture energy measures18</td>
</tr>
<tr>
<td>Texture-based</td>
<td>Snakes integrated with sticks algorithm19</td>
</tr>
<tr>
<td>Pixel classifier</td>
<td>DDC20</td>
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<tr>
<td>Model-based</td>
<td>Snakes with shape restrictions based on the wavelet transform21,22</td>
</tr>
<tr>
<td>Deformable contour models</td>
<td>Feed-forward neural networks23</td>
</tr>
<tr>
<td>Statistical models</td>
<td>MRF24</td>
</tr>
<tr>
<td></td>
<td>Feature modeling25</td>
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</table>
In their proposed method, Lee et al\textsuperscript{14} and Chen et al\textsuperscript{15} used low-pass filters to smooth the image; after that, the center of the prostate is estimated. A search process in radial directions from the estimated center is then performed to locate the prostate boundary by using derivative edge detectors. The 2D contour is obtained by properly linking the detected edges. Unfortunately, unwanted structures, such as the bladder neck and pelvic bones, are usually included.\textsuperscript{7}

Pathak et al\textsuperscript{7} used an edge-based technique for outlining the prostate boundary. Their algorithm comprises 3 stages. First an algorithm called sticks\textsuperscript{28} is used to enhance contrast and at the same time reduce speckle in the TRUS. Then the sticks-enhanced image is further smoothed by an algorithm called weak membrane fitting, which is similar to the anisotropic diffusion filter.\textsuperscript{29} Finally, some basic prior knowledge of the prostate, such as shape and ultrasonographic appearance, as addressed previously,\textsuperscript{11,12} is used to detect the most probable edges describing the prostate. This detected prostate boundary is presented as a visual guide to the observer, followed

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure2.png}
\caption{Example of the contour detection process using maximum/minimum filtering. a, Original ultrasonographic image; b, blurred and compressed image; c, local minimum of the image; d, local maximum; e, gradient in the direction from the minimum; f, gradient in the direction of the maximum; g, second derivative in the gradient direction; h, zero crossings in the second derivative; i, edge strength; j, edge strength masked by the zero crossings; k, selected contour; l, ultrasonographic image with the projected contour. Reprinted with permission from H. Wijkstra, PhD (University Medical Center Nijmegen, Nijmegen, the Netherlands).}
\end{figure}
by manual editing. Figure 3, a and b, shows the edge detection result of a midgland image before and after the knowledge-based filtering. The detected edges are overlaid on top of the image (Fig. 3c) and then presented as a visual guide to the observers for manually delineating the prostate boundary (Fig. 3d).

Liu et al.\textsuperscript{16} developed a radial bas-relief (RBR) method, which is adopted and extended from a darkroom technique used in conventional photography (i.e., bas-relief), to segment the prostate boundary from TRUS. The proposed method consists of 3 steps: (1) image inversion, (2) image panning (to provide a position offset register by moving every pixel radically from the center of the image by a certain distance), and (3) dual-image addition (superimposing positive and negative images). Figure 4c shows the result obtained by RBR. It can be seen that the boundary of the prostate is clearly highlighted, and the image looks binarylike. The resulting image is then binarized by thresholding (Fig. 4d), and dilation and erosion operators are used to smooth the boundary area. The smoothed, binarized image is then inverted again to switch the boundary areas to the foreground (Fig. 5a).

**Figure 3.** Edge-guided boundary detection. \textbf{a}, Detected edges before a priori knowledge-based filtering; \textbf{b}, edge image after removal of false edges with the use of knowledge-based filtering; \textbf{c}, edges overlaid on top of the prostate image; \textbf{d}, final boundary delineation on the prostate image. Reprinted with permission from Y. Kim, PhD.
Foreground areas with boundary lengths greater than a given number of pixels are then labeled as boundary areas (Fig. 5b). To thin these boundary areas, a skeletonizing process is introduced. The prostate boundary (Fig. 5d) is finally produced by complementing the skeleton image (Fig. 5c) through a one-dimensional polynomial fitting process. Alternatively, the contour complementation can be fulfilled with harmonics. Figure 6 illustrates the process of harmonics curve fitting. A major problem of the RBR method is that the RBR center should be close to the boundary centroid to produce a good result. If the image center and the object boundary centroid have a big deviation, the RBR method would fail to detect the desired boundary.
**Texture-Based Detection Methods**

Another image segmentation technique for boundary detection is texture discrimination.\(^{30}\) Rather than trying to find the edges in an image, texture discrimination attempts to characterize regions of an image on the basis of measures of texture. It can also produce an edge map of an image, as with edge detection, by creating a border between regions determined to have different textures. In other words, the edge map created in terms of texture discrimination is derived by examining regions rather than edges.

In their work, Richard and Keen\(^{18}\) presented a texture-based segmentation method to extract the prostate boundary by segmenting 2D images of the prostate gland into prostate and non-prostate regions. The texture-based method is in fact a pixel classifier based on 4 texture energy measures associated with each pixel in the image. A clustering procedure is used to label each pixel in the image with the label of its most probable class. Although some progress has been made on the ability of their algorithms to delineate the prostate boundaries, Richard and Keen\(^{18}\) have acknowledged that the effect of using texture information is marginal.

**Model-Based Detection Methods**

Most recent research has shown that model-based segmentation methods are more efficient and powerful in delineating object boundaries.\(^{31}\) These model-driven image analysis techniques integrate some prior knowledge, such as anatomic information, physical characteristics of the object, and radiologic features of imaging, into the model, thus improving the boundary detection algorithms. This section reviews 2 different classes of model-driven techniques that have been applied to prostate boundary detection: (1) methods based on deformable contour models and (2) methods based on statistical models.

**Methods Based on Deformable Contour Models**

Deformable contour models are physically motivated, model-based techniques for delineating object boundaries by using closed curves or surfaces that deform under the influence of internal and external forces. Deformable contour models were first introduced as tools for image segmentation by Kass et al.\(^{32}\) In their formulation, known as active contour models or snakes, image segmentation is considered an energy minimization problem. When an active contour model is placed on an image, solving corresponding equations yields positions along a curve that minimize the energy function. Many sections of the curve will follow edges in the image, but the internal energy constraints will also keep the curve relatively smooth. During the past few years, a deformable contour model has been extensively investigated as an appealing tool for imaging segmentation or boundary detection.

In their work, Pathak et al\(^{19}\) presented an algorithm based on snakes to detect the prostate boundary from TRUS. First the sticks algorithm\(^{28}\) is used to selectively enhance the contrast along the edges, and afterward a snake model is applied. This integrated algorithm requires an initial curve input by the user for each ultrasonographic image to initiate the boundary detection process, and the results show their sensitivity to the curve initialization. When an initial contour is reasonably close to the prostate boundaries, the algorithm successfully delineates the prostate boundaries in an image.

To efficiently detect the prostate boundary, Ladak et al\(^{20}\) developed a method based on a deformable contour model, named the discrete dynamic contour (DDC).\(^{33}\) In this method, initialization requires the user to select only 4 points (Fig. 7a) from which the outline of the prostate is estimated by cubic interpolation functions and shape information. To improve the model’s performance, gradient direction information is used during deformation to push the model toward the boundaries. However, the success of their approach is dependent on the careful initialization of the contour (Fig. 7b), which requires the user to select points on the prostate boundary. To overcome this drawback, the authors added a tool to edit the detected boundary and then redefine it (Fig. 7, c and d).

Knoll et al\(^{21,22}\) attempted to address the problem of initialization for deformable contours and modeling for segmentation of the prostate in ultrasonographic images. They proposed a technique to restrict elastic deformation according to particular prostate shapes of a closed planar curve using localized multiscale contour parameterization based on one-dimensional dyadic wavelet transform.\(^{34}\) For this purpose, they used the multiscale parametric contour analysis to determine the wavelet transform coefficients and then to reconstruct the contour. The difference of the original deformed contour and the
reconstructed contour was further used to define inner snake forces. This restricted contour deformation and its initialization by template matching are performed in a coarse-to-fine segmentation process based on multiscale image edge representation, which contains the important edges of the image at various scales. A comparison of detected results between conventional unrestricted snakes and the proposed shape-restricted snake method is shown in Figure 8. It is very clear that this method provides much better results compared with conventional snakes.

Methods Based on Statistical Models
The idea behind the statistical models for image segmentation is to code the variations of the selected parameters, which are used to describe the detected object, in an observed population (the training sets) and to characterize this in a compact manner. The parameters are estimated from the available segmented images and are used for segmentation of new images. Furthermore, the results from new segmentations can be incorporated into the model, thus updating a priori information available to the system.

In their work, Prater and Richard described a method for segmenting TRUS images of the prostate using feed-forward neural networks. They presented 3 neural network architectures for this purpose. Each of these networks was trained with the use of a small portion of a training image segmented by an expert sonographer. This method could provide a good result of segmentation; however, it requires extensive teaching sets, so it greatly complicates the detection procedure. In addition, incorporating user-specified boundary information into the neural networks is also a difficult task.

Figure 7. Prostate boundary detection by DDC. a, Initial DDC; b, after initial deformation; c, 3 points (indicated by squares) were edited and clamped; d, after second deformation. Reprinted with permission from H. M. Ladak, PhD (University of Western Ontario, London, Ontario, Canada).
Lorenz et al\textsuperscript{24} used the Markov random field (MRF) to extract the prostate boundaries. They adapted and extended a probabilistic method that was first described by Dias and Leitão\textsuperscript{35} in 1996 for the estimation of heart wall motion and thickness. They assumed the contour sequence to be a 2D first-order Markov random process, and prior knowledge about the contour shape is incorporated by clique potentials defined on a neighborhood system. The contour is estimated iteratively on the basis of the maximum a posteriori principle and produced finally in this way. A difficulty associated with the MRF method is proper selection of the parameters controlling the strength of spatial interactions. The other drawback is its intensive computational load.

Wu et al\textsuperscript{25} developed a feature-modeling method, which is derived from conventional point distribution modeling\textsuperscript{36} to detect the prostate boundary automatically. In their model, some specific information about the prostate, such as the shape, actual size, relative position to the ultrasonic probe, and orientation of its boundary, was successfully integrated. The authors proposed a simple automatic labeling scheme (Fig. 9) to sample the boundary and model it. The black round circle at the bottom shows the position of the ultrasonic probe, and the area at the centroid of each prostate boundary sample was calculated first. Then the boundaries were labeled clockwise at equal angular increments along the shape. After that, a prostate boundary model is then built up from the sample vectors. The modeling on 27 sample boundaries captures 9 principle variations of the boundary. A new possible prostate boundary can be produced from a weighted sum of the 9 principal variations and the mean boundary. Because 9 weights need to be decided to reconstruct a boundary, a genetic algorithm is used to optimize the decision process. To improve the genetic algorithm searching process, both image gradient magnitude and direction are used. Figure 10 shows the results detected by the feature-modeling method. According to the evaluation of Wu et al\textsuperscript{25} this method has achieved good accuracy and robustness.

However, the feature-modeling method is only suitable for some particular shape-based prostate images. The specifications in the model limit its application to general prostate boundary detection. Moreover, the proposed method requires that the central point of the ultrasonic probe area should be visible in the image; unfortunately, in most cases, it is not captured.

\textbf{Figure 8.} Comparison of detected results between conventional unrestricted snakes (top row) and the proposed shape-restricted snakes method (bottom row). Reprinted with permission from M. Alcaniz, PhD. (Universidad Politecnica de Valencia, Valencia, Spain).
Three-dimensional Prostate Surface Detection From Sonographic Images

Limitations of 2D Sonography
Currently, most prostate diseases are readily diagnosed with conventional 2D ultrasonographic equipment. However, conventional 2D TRUS has some serious limitations. They arise because only 1 thin slice of the prostate can be viewed at any time, and the location of this image plane is controlled by physically manipulating the transducer orientation. As a result, the diagnostician, therapist, or surgeon must mentally integrate many 2D images to form an impression of the 3D anatomic and pathologic characteristics. This process is time-consuming and inefficient but, more important, variable and subjective, possibly leading to incorrect decisions in diagnosis, planning, and delivery of therapy. Moreover, it is difficult to place the 2D image plane at a particular location within an organ and even more difficult to find the same location again later. To overcome these limitations, 3D TRUS of the prostate has been developed. Consequently, 3D prostate surface detection techniques are attracting more and more attention from the image-processing community.

Methods for 3D Prostate Surface Detection
Two kinds of methods for detecting the 3D prostate surface have been reported in the literature. One is reconstructing the 3D prostate surface from a sequence of 2D contours detected in parallel cross-sectional images, we call it a pseudo-3D approach. The main disadvantages of this kind of method are that (1) large gaps in boundaries of 1 slice usually lead to poor detected results; (2) segmentation of a slice along different axes may lead to different results; and (3) reconstruction of the surface and its properties from 2D contours may lead to inaccurate results. These drawbacks derive from the limitation that they cannot use the information in neighboring slices to improve the detection process. The other method is directly using 3D models to detect the prostate surface, in which all computation is carried out in 3D space; we call it a volume approach. In this section, we focus on volume approach segmentation.

Ghanei et al. proposed a 3D-deformable surface model for automatic segmentation of the prostate. In their method, a model is initialized from a few initial contours that are drawn on different slices. These initial contours, which are outlined as polygons, are similar to the DDCs. The model creates a closed initial surface from the drawn contours (Fig. 11), and then it converges from this initial shape to its equilibrium iteratively by movement of its vertices under a weighted sum of internal and external forces. To improve the robustness and speed, the entire model is applied in a multiscale scheme. As
shown in their work, the agreement between the model contour and the manual contour in several slices is quite good. However, to produce good results, typically 40% to 70% of the slices are needed to define the initial surface. This initialization process is not easy to deal with, especially when the number of slices is quite large. Moreover, this method is still subject to the initialization sensitivity problem.

Recently, implicit representations of deformable models, including a level set method, have been widely used to reduce the initialization sensitivity. The most attractive advantage of the level set method is that the whole segmentation procedure is fully automatic when given an initial zero level set (hypersurface). Furthermore, the initial hypersurface can be chosen freely; that means it does not need to be put close to the desire boundary, as in traditional parameterization models. This relieves the user interaction and consequently improves efficiency. In their work, Shao et al. took advantage of this feature to detect the prostate surface from 3D TRUS images. Because of the aforementioned poor quality of ultrasonographic images, the boundary feature of the object is usually not salient enough, and the image gradient information is weak. It causes the “boundary-leaking” problem when the original level set method is applied to detect the 3D prostate surface (Fig. 12). To remedy the leaking problem, Shao et al. integrated the region information instead of the image gradient into the level set method to improve model...
performance. Figure 13 gives the result detected by this method from a 256 × 256 × 256 TRUS image, and Figure 14 shows a comparison of the detected contours and manual contours in 2D cross-sectional images.

A good example of detection of the 3D prostate surface based on deformable models can be created in 3DView (GE Medical Systems, Waukesha, WI), personal computer software for diagnostic analysis and 3D rendering of examination data produced on a Voluson 530D MT system (GE Medical Systems). The surface is constructed on the basis of so-called virtual organ computer-aided analysis technology by 3D triangulation of the 2D contours detected in each plane, which rotates around a fixed axis (main contour axis; Fig. 15a, red dotted line). In fact, all the 2D contours are produced from the deformation of a prior prostate shape integrated in virtual organ computer-aided analysis. Figure 15a illustrates the selection of 2 contour points (selected by the user with a mouse) on the rotation axis, and Figure 15b shows the detected result.

3DView provides an efficient tool for 3D prostate surface detection; however, its limitations are also obvious. The detected result is quite sensitive to the selection of the 2 contour points on the rotation axis and the selection of the reference images (Fig. 15a, A–C). Figure 16 shows the result obtained from a different reference image A. It is clear that the results vary considerably when a different reference image is selected.

Algorithm Verification

Before the detected boundaries are used in clinical decisions for the diagnosis and treatment of prostate diseases, a very important task is to validate the accuracy of the algorithm’s performance, because any large disagreement between the detected boundaries and the real targets might result in severe damage. To evaluate the efficiency of the prostate detection algorithms, various methods have been proposed in the literature.7,19–22,25,26

Pathak et al7 used distance-based metrics (the Hausdorff distance44,45 and the mean absolute distance46) to measure the disagreement between multiple observers’ segmentation and the disagreement between computer-aided outlining and fully manual outlining compared with the average interobserver disagreement during fully manual outlining. Although the Hausdorff distance measures the worst possible disagreement, the mean absolute distance estimates the disagreement averaged over the 2 contours. The assessment of Pathak et al7 showed that automatic and semiautomatic segmentation of the prostate indeed leads to better consistency.

Conversely, Wu et al25 used the fractional area (Fig. 17) to estimate the disagreement between 2 contours, and the assessment scheme is shown in Figure 18. The average disagreement between the outline of the computer and the outlines of experts is $D_{av} = (D_1 + D_2)/2$, where $D_1$ and $D_2$ denote the outline disagreement between the computer and experts 1 and 2, respectively. Then $D_{av}$ is compared with $D_1$, the disagreement between the 2 experts, to determine whether the computer-aided outlining agrees with the results provided by the experts. Apparently, this assessment scheme is a special case from a previous joint agreement study.44
Ladak et al\textsuperscript{20} used both distance-based\textsuperscript{44} and area-based\textsuperscript{47} metrics to compare semiautomatically outlined boundaries with manually outlined boundaries. The distance-based metrics are obtained by calculating the difference in length of the vertices from the reference point (Fig. 19), as described previously\textsuperscript{48}. On the basis of $d_j(\theta)$, 3 quantities (mean difference, mean absolute difference, and maximum difference) describing the difference between the 2 sets of boundaries are calculated to determine the agreement between the algorithm and the experts. Meanwhile, 3 different areas defined by the 2 corresponding outlines (true-positive area, which is the common region between the manual outline and the algorithm outline; false-
positive area, the region enclosed by the algorithm outline but outside the manual outline; and false-negative area, the region enclosed by the manual outline that is missed by the algorithm) are also used to estimate the accuracy further. Similarly, besides measuring the average distance of the model and manual contours, Ghanei et al\textsuperscript{26} used a similarity measure (area based), which was based on \( \kappa \) statistics\textsuperscript{49} to compare the model results with the manual segmentation.

Pathak et al\textsuperscript{19} used planimetric volumetry\textsuperscript{8} to calculate the prostate volume after the boundaries were identified. These volumes are then compared against those manually measured by 3 experts. As addressed by Pathak et al\textsuperscript{7} comparing volumes is not a stringent evaluation criterion, because it is a cumulative function of the delineations made on each image over the entire prostate volume. Even very different outlines made by 2 observers could result in the same volume estimates. Therefore, contour comparison is still indispensable for 3D algorithm assessment. In their work, Knoll et al\textsuperscript{21,22} used 3 complementary error measures for validation: (1) the volume difference (\( VD \)), which is defined as the number of different voxels between the manual segmented reference volume (\( RV \)) and the automatic segmented volume (\( AV \)) of the whole scan set of a patient with respect to \( RV \):

\[
VD = \frac{1}{2} \left( (RV \cup AV) - (RV \cap AV) \right)
\]

(2) the contour difference, which is calculated as the mean dis-

Figure 14. Comparison between level set–detected contours and manual contours in 2D images. a, Cross-sectional slices; b, detected contours; c, manual contours; d, contour comparison.
distance of the manually drawn contour pixel to its nearest automatically detected contour pixel; and (3) the absolute volume difference (AVD), which is simply the relative difference between the 2 volumes \( \text{AVD} = |RV - AV|/RV \).

Clearly, contour disagreement in two dimensions can be measured by the distance-based metrics (calculating the difference in the lengths of 2 points on the corresponding contours) or area-based metrics (calculating the difference of pixels enclosed in 2 contours) alone; nevertheless, the verification would be more reliable if both were used. As for validating 3D algorithms, both volume disagreement and contour disagreement should be measured.

**Discussion**

In the previous sections we have surveyed the considerable work on prostate boundary detection from ultrasonographic images. All these algorithms have a certain degree of clinical utility; however, they have their own disadvantages or limitations, yet they are not widely used nowadays. Manual contouring has been the dominant method up to now. This section summarizes the key issues and projects possible future research.

**Model-Based Method Development**

It has been proved that model-based methods are more efficient and powerful in object boundary delineation\(^3\); hence researchers currently are mainly focusing on model-based method development for prostate boundary and surface detection.\(^{19-27}\) Compared with the edge-based detection methods, although more complicated and still needing improvement, model-driven methods elide the edge selection and linking process, which needs to be carefully designed and requires more prior knowledge as well to consequently improve efficiency. As a result, model-based method development would become one of the most important tasks in this research area.

**Allowing for Manual Editing**

Definitely, automatic (partially or fully) detection can potentially increase the speed, consistency, and reproducibility of the process. However, its accuracy is difficult to guarantee because of the poor quality of ultrasonographic images. For computer-assisted surgery, this may result in injuries to the patient. Consequently, the most successful methods will likely be those that drastically decrease the labor intensiveness of boundary detection tasks through partial automation but still allow for interactive guidance or editing by medical experts. Ladak et al\(^20\) and Pathak et al\(^1\) have recognized this issue and permit the manual editing to refine the final detected boundaries. By providing the manual editing tools, the users (surgeons and radiologists) can refine the final contours or surfaces by adjusting the control points (vertices) to help them make correct decisions.
Taking Advantage of 3D Ultrasonographic Images

In the last few years, technology has progressed to make 3D ultrasonographic imaging a viable tool. Previous reports have shown that 3D ultrasonography has advantages over conventional techniques and that it will play an increasingly important role in prostate disease diagnosis and treatment. Although from sequential cross-sectional 2D boundaries we can reconstruct a 3D prostate surface, those algorithms, which would be able to take advantage of 3D information, would be more robust and accurate.

Incorporating Both Statistical and Shape-Based Information

Because of the poor quality of ultrasonographic images, edge or region information is usually not enough to be used to extract prostate boundaries. To improve accuracy and robustness, information on general shape, location, and orientation as well as intensity distribution in the prostate should be incorporated into the models. These could be in the form of initial conditions, data constraints, constraints on the model shape parameters, or model-fitting procedures. The results encourage us that the use of both statistical and shape-based information to guide prostate boundary detection might improve the algorithm's performance very well. In fact, 3DView, to our knowledge the only available commercial source, integrates shape-based information in its model for more efficient detection of the prostate surface.

Standard for Verification

It is very clear that all the evaluation methods described in “Algorithm Verification” need the experts’ manually outlined boundaries as references. However, manual contouring itself is variable both between and within observers; although a mean contour of manually outlined contours produced by multiple observers can be used to reduce the variation, this evaluation criterion is not reliable enough. An alternative method is to use the boundaries outlined from magnetic resonance images and photographs of the prostate obtained through prostatectomy as references for measuring the disagreement. Although this is a difficult task and still at its start point, we think that this criterion may be more objective and reliable; hence we call it the standard of reference.
Conclusion

With the number of men seeking medical care for prostate diseases rising steadily, the need for a fast, accurate prostate boundary detection tool has increased accordingly. Automatic (partially or fully) prostate boundary detection methods provide robust, consistent, reproducible results with a certain degree of accuracy. It is unlikely that automatic prostate boundary detection methods will ever replace physicians, but they will likely become crucial elements in prostate disease diagnosis and treatment, particularly in computer-assisted surgery. Continued development and refinement of these methods should remain an important area of research in the foreseeable future. Those model-based methods that minimize user involvement but still allow for interactive guidance by experts will likely be most immediately successful.

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