The Various Essential Techniques to Detect Prostate Cancer

Miss. Vinitha kumari. G
IV Sem, M.Tech, Department of Computer Science & Engineering,
Akshaya Institute of Technology, Lingapura, Tumkur 572 106, Karnataka, India

***Abstract*— Prostate segmentation is a challenging task, and the challenges significantly differ from one imaging modality to another. Low contrast, speckle, micro-calcifications and imaging artifacts like shadow poses serious challenges to accurate prostate segmentation in transrectal ultrasound (TRUS) images. This paper discusses some of the common techniques used by the researchers to identify the presence of prostate cancer from image processing viewpoint. It also discusses challenges based method and supervised and un-supervised classification based on algorithm along with the most recent study conducted in this domain.**

Keywords*: - *Prostate cancer, MRI

I. Introduction

Imaging for prostate carcinoma can serve several clinical goals. First, it can assist in assessing the primary or recurrent tumor within the prostate gland, as well as tumor size, multimodality, extra capsular extension, seminal vesicle extension, neurovascular bundle involvement, and bladder involvement. Second, imaging can be used to assess metastatic disease such as spread to lymph nodes and bones. Third, imaging is used to guide interventions such as prostate biopsies or computed tomography (CT)-guided biopsy of suspicious lymph nodes. Fourth, functional or metabolic imaging could potentially assess tumor aggressiveness or other parameters that correlate with outcome, although such techniques have not yet entered routine clinical practice. It is hoped that these novel imaging methods will be superior to the current standard means in assessing mortality, tumor size, and therapeutic response to targeted therapies. This review focuses on the main imaging methods and their use for these purposes.

The National Comprehensive Cancer Network clinical practice guidelines show a fairly limited role for imaging in patients with prostate carcinoma. [1]According to these guidelines, imaging is largely used to evaluate metastatic disease, with a limited role for end rectal magnetic resonance imaging (MRI) in patients who have received radiation therapy but have evidence of failure by prostate-specific antigen (PSA) level. According to these recommendations, low-risk prostate cancer requires no imaging; however, actual adherence to these guidelines by urologists is highly variable. [2] Many more applications and types of imaging have been explored, with a plethora of suggested imaging applications for the management of prostate carcinoma. Many of these, such as investigational nuclear medicine agents, are exploratory, but others, such as end rectal MRI for initial staging, have been the focus of numerous studies.

Reports on the diagnostic performance of some of these techniques vary widely in the literature, particularly regarding MRI. In some respects, this resembles the decline effect [3] or other statistical biases, [4] but methodological aspects assess diagnostic performance in the prostate that may give rise to these varying results. To determine the accuracy of a diagnostic technique such as MRI in locating a tumor within the prostate, it is common to divide the prostate into multiple areas or segments and determine the presence or absence of the tumor in each segment. These results can be correlated with the absence or presence of tumor on MRI. If the prostate specimen is distorted during processing or if discordance exists between the orientation of the pathological specimen to MRI, then the diagnostic accuracy will be poor, not related to the actual performance of the technique.[5],[6] Different results can be obtained, for example, when exact correspondence is required rather than when approximate correspondence is required. These methodological problems may lead to varying results and introduce bias in reported results for the diagnostic performance of MRI and for other diagnostic techniques. Turkbey et al[7] found a 61% sensitivity rate for the detection of tumors larger than 3 mm in size on T2-weighted images sing a stringent correlation and 94% sensitivity rate for less stringent correlation. The magnitude of this discrepancy indicates that correlating imaging findings with histology is not as straightforward as one might think.

II. Prostate segmentation methods

The prostate cancer methods according to the theoretical computational approach taken to solve the problem. We believe that such a classification successfully points out the key algorithmic similarities and dissimilarities, highlighting their strengths and weaknesses at the same time. We globally classify the methods into different strategies: contour and shape based, region based, supervised and un-supervised classification methods based, and hybrid methods. We further refine these groups to produce a more local classification schema. For instance, contour and shape based methods are further classified into edge, probabilistic filters and Deformable models. We have grouped the prostate segmentation methods in four different groups, according to the information used to guide the segmentation. Broadly,

- *Contour and Shape based Methods:* These methods use prostate boundary/edge information to segment the prostate cancer. Since often edge information is unreliable in TRUS and CT images and in the base and the apex region of the

MR images, prior shape information is incorporated to provide better results.

○ *Region based methods:* These 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.

○ *Supervised and un-supervised classification methods:* These methods use features like intensity or higher dimensional features like filter responses to cluster and/or classify the image into prostate and background regions. The objectives of such methods are to group similar objects together based on the feature vector. 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.

○ *Hybrid methods:* The objective of the hybrid methods is to 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.

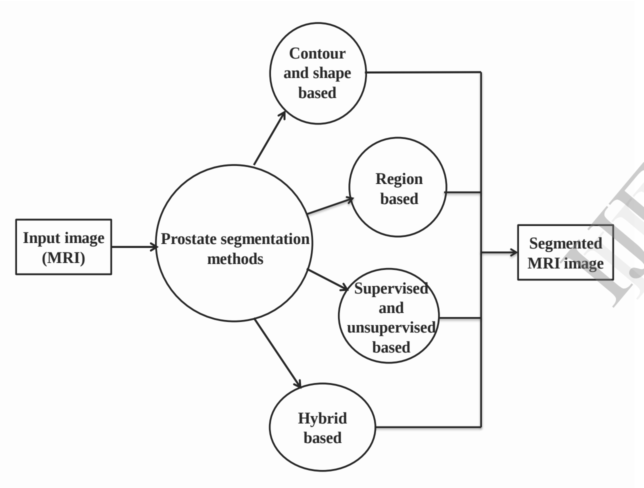

Fig.1. The overall Data Flow Diagram of Prostate Segmentation Methods.

III. Challenges in Processing Prostate Tissue Slide Images

We summarize the major challenges in processing and interpreting prostate tissue slide images:

1. The first challenge relates to the large image size, as discussed above. We address this problem by processing the images at a lower magnification. Our methods for gland segmentation, gland classification, and tissue image classification obtain good results for images at 5× magnification, which are comparable to results for images at 20× magnification.
2. The second challenge is the large variations, both in shape and appearance, in the glandular structures, which makes model-based approaches such as Active Shape Model [8] or Active Appearance Model [9] inapplicable. Our proposed gland segmentation method is a model-free approach which is able to capture important structures of the glands regardless of their variations in size and shape.
3. The third challenge is the large color variations in the tissue structures in the image. This can be due to several reasons such as: (i) differences in staining (tissue is either over stained or understand), (ii) long term storage which makes the stain fade overtime, (iii) different types of tissue scanners.

IV. Contour and Shape Based Segmentation

Contour and shape based methods exploit contour features and shape information to segment the prostate. These methods can be categorized into edge based methods, probabilistic filters and deformable model segmentation techniques. Deformable model based techniques are further classified into active contour models, deformable meshes, active shape models, level sets and curve based segmentation. The following subsections discuss individually each of these categories.

○ *Edge based segmentation:* - Extracting edges in an image using gradient filters like Prewitt, Robert, Sobel, Shen and Castan and Canny, is a popular practice in image processing. However, in presence of noise gradient filters often detect false edges and also the detected edges are often broken. Although computationally expensive edge linking algorithms have to be designed to produce connected edges, in most cases is necessary to combine edge based algorithms with intensity based and texture based information for accurate segmentation [10].

As an example the sobel edge considered. The partial derivatives of the Sobel operator are calculated using (1) and (2).

$$Gx = (a_6 + 2a_5 + a_4) - (a_0 + 2a_1 + a_2) \quad (1)$$
$$Gy = (a_2 + 2a_3 + a_4) - (a_0 + 2a_7 + a_6) \quad (2)$$

Therefore the Sobel masks are:

-1	-2	-1
0	0	0
1	2	1

G_x

-1	0	1
-2	0	2
1	0	1

G_y

Here, Gx (vertical odd 3×3 mask) and Gy (horizontal odd 3×3 mask) is applied on the image and Gx, Gy is found excluding the boundaries. Then absolute magnitude gradient is found.

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a) b)

Fig.2. Example of Edge based segmentation. **a)** Input image. **b)** Sobel edge (output image).

- *Probabilistic Filtering:* - Probabilistic filters like the Kalman filter [11], the probabilistic data association filter (PDAF) [12] and particle filters [13] have been successfully used to segment images. These methods model the boundary of an organ as a probabilistic trajectory of a moving object where the motion is governed by a dynamic model subject to a particular uncertainty. Segmentation algorithms based on probabilistic filters are fast as no optimization framework is necessary [14]. However, these methods may be sensitive to the initialization and the extension to 3D segmentation is complicated. Hence, to the best of our knowledge no method has been developed for 3D segmentation of the prostate in MR and in CT images.

- *Deformable model based segmentation:* Deformable model segmentation techniques are influenced by theories from geometry, physics and mathematical optimization. Geometry imposes constraints on the model shape, physical theories guide the evolution of the shape in space, and optimization theory guides the model to fit the available data [15]. Deformable models are often associated with internal and external energies. External energies propagate the deformable model towards the object boundary and internal energies preserve smoothness of the contours during deformation. Internal and external energies associated with a deformable model are combined and included in an energy minimization framework to segment anatomical structures by warping to the edges with minimum deformation away from their mean shape. The methods proposed in a deformable model framework may be broadly classified into active contour models, deformable mesh, active shape models, level sets and curve fitting.

We use the technique of matching a deformable model to an image by means of energy minimization. A snake initialized near the target gets refined iteratively and is attracted towards the salient contour. A snake in the image can be represented as a set of *n* points.

$$V_i = (x_i, y_i) \quad (3)$$

Where $i = 0....n-1$

The external energy of the snake can be written as

$$E_{external} = E_{\mathrm{Im}age} + E_{con} \quad (4)$$

Where, $E_{\mathrm{Im}age}$ denotes the image forces acting on spline and E_{Con} serves as external constraint forces introduced by user. The combination of $E_{\mathrm{Im}age}$ and E_{Con} can be represented as $E_{external}$, which denote the external energy acting on the spline.

The Internal Energy of the snake can be written as

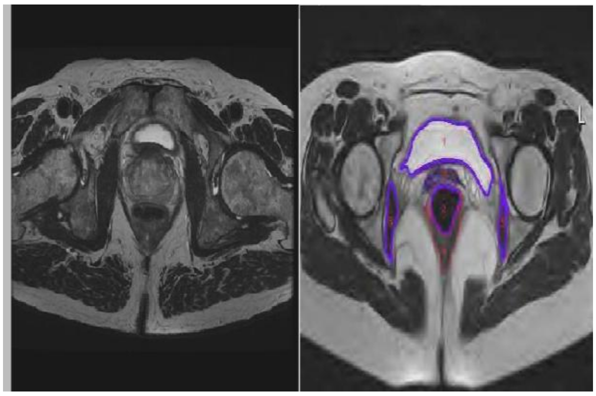
$$E_{Internal} = E_{Cont} + E_{curu} \quad (5)$$

Where, $E_{Internal}$ represents the internal energy of the spline (snake) due to bending, E_{Cont} denotes the energy of the snake contour E_{curu} denotes the energy of spline curve.

$$E_{\mathrm{internal}} \left(\alpha(S) |V_s(S)|^2 + \beta(S) |V_{SS}(S)|^2 \right) / 2$$

$$= \left(\alpha(S) \left\| \frac{d\bar{v}}{ds}(S) \right\|^2 + \beta(S) \left\| \frac{d^2\bar{v}}{ds}(s) \right\|^2 \right) / 2 \quad (6)$$

Here, the first-order term makes the snake act like a membrane and second-order term makes it act like a thin plate. Large values of $\alpha(S)$ will increase the internal energy of the snake as it stretches more and more, whereas small values of $\alpha(S)$ will make the energy function insensitive to the amount of stretch. Similarly, large values of $\beta(S)$ will increase the internal energy of the snake as it develops more curves, whereas small values of $\beta(S)$ will make the energy function insensitive to curves in the snake. Smaller values of both $\alpha(S)$ and $\beta(S)$ will place fewer constraints on the size and shape of the snake.



a) **b)**

Fig.3. Example of Deformable model based segmentation. **a)** Input image. **b)** Deformable segmentated image (purple).

V. SUPERVISED AND UN-SUPERVISED CLASSIFICATION BASED ALGORITHMS

In pattern recognition feature could be defined as a measurable quantity that could be used to distinguish two or more regions. More than one feature could be used to differentiate different regions and an array of these features is known as a feature vector. The vector space associated with feature vectors is known as feature space. Supervised and un-supervised classification (PR) based techniques aim at obtaining a partition of the feature space into a set of labels for different regions. Primarily classifier and/or clustering based techniques are used for the purpose. Classifiers use a set of training data with labeled objects as a priori information to build a predictor to assign label to future un-labeled observations. In contrast, in clustering methods a set of feature vectors are given and the goal is to identify groups or clusters of similar objects on the basis of the feature vector associated with each. Proximity measures are used to group data into clusters of similar types.

- *Classifier based segmentation:*- In classifiers based segmentation the prostate is seen as a prediction or learning problem. Each object in a training set is associated with a response variable (class label) and a feature vector. The training set is used to build a predictor that can assign class label to a object on the basis of the observed feature vector.
- *Clustering based segmentation:* - The goal of clustering based methods is to determine intrinsic grouping in a set of un-labeled data based on some distance measures. Each data is associated with a feature vector and the task is to identify groups or clusters of similar objects on the basis of the set of feature vectors. The number of groups is assumed to be known and implicitly one must select the relevant feature, distance measure and the algorithm to be used.

VI. EXISTING WORK

Mehrabian et al., [16] presented an adaptive complex independent component analysis method is developed to identify and separate AIF from complex DCE-MRI data. The results are compared with a previously introduced AIF estimation method that applied ICA to magnitude DCE-MRI data. Using simulation and experimental phantom studies it is shown that using both magnitude and phase data (complex) results in a more robust and more accurate AIF measurement algorithm.

Mehrabian et al., [17] studied a method is introduced to calculate the intravascular concentration in the prostate tissue using an adaptive complex independent components analysis (ACICA) method and to correct this curve for the early phases of the passage of the contrast agent through tumor vasculature. The results are applied to DCE-MR images of the prostate of a 70 year old prostate cancer patient and the calculated map is examined using tumor location defined by multi-parametric MRI.

Fan and Karczmar [18] purposed of this research was to develop a novel numerical procedure to deconvolute arterial input function from contrast concentration vs. time curves and to obtain the impulse response functions from dynamic contrast enhanced MRI data. Numerical simulations were performed to study variations of contrast concentration vs. time curves and the corresponding impulse response functions.

Sintra [19] have depended on a contrast function that serves as a rotation selection criterion. One of the contrasts proposed is built from the mutual information of standardized observations. For practical purposes this contrast is approximated by the Edge worth expansion of the mutual information, and consists of a combination of third- and fourth-order marginal cumulates.

Hyvärinen et al., [20] proposed that this residual dependence structure could be used to define a topographic order for the components. In particular, a distance between two components could be defined using their higher-order correlations, and this distance could be used to create a topographic representation. Thus they obtain a linear decomposition into approximately independent components, where the dependence of two components is approximated by the proximity of the components in the topographic representation.

Ganesh et al., [21] introduced the fundamentals of BSS and ICA. The mathematical framework of the source mixing problem that BSS/ICA addresses was examined in some detail, as was the general approach to solving BSS/ICA.

As part of this discussion, some inherent ambiguities of the BSS/ICA framework were examined as well as the two important preprocessing steps of centering and whitening. Specific details of the approach to solving the mixing problem were presented and two important ICA algorithms were discussed in detail. Finally, the application domains of this novel technique are presented. Some of the futuristic works on ICA techniques, which need further investigation are discussed.

Ahmad and Ghanbari [22] reviewed independent component analysis (ICA) technique based on Kurtosis contrast function. They briefly present the common independent component analysis algorithms that use Kurtosis as a criterion for non-Gaussian. Based on the literatures, they compare these algorithms in terms of performance and advantages.

Kolenda and Hansen [23] analyzed the feasibility of independent component analysis (ICA) for dimensional reduction and representation of word histograms. The analysis is carried out in a likelihood framework which allows estimates of the loadings (source signals), the mixing

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matrix and the noise level. In the face of noisy signals, the estimated sources are non-linear functional of the observed signals, in contrast to the linear noise free case. They also discuss the generalizability of the estimated models and show that an empirical test error estimate may be used to optimize model dimensionality, in particular the optimal number of sources.

Sararu et al., [24] described a new classification methodology based on the use of Independent Component Analysis and Wavelet decomposition (ICAW) techniques. An ensemble system of classifiers is built such that each classifier independently decides the assignation of the test examples on several representations resulted by taking projections computed by wavelets and Independent Component Analysis.

Chen et al., [25] present a realistic and fast method, GHICA, which overcomes the limitations in multivariate risk analysis. The idea is to first retrieve independent components (ICs) out of the observed high-dimensional time series and then individually and adaptively fit the resulting ICs in the generalized hyperbolic (GH) distributional framework. For the volatility estimation of each IC, the local exponential smoothing technique is used to achieve the best possible accuracy of estimation.

VII. CONCLUSION

This paper reviewed the methods involved with prostate cancer detection. We also presented challenges in processing prostate tissue slide images, supervised and un-supervised classification based algorithms, contour and shape based segmentation. Finally, a discussion on choosing an appropriate segmentation methodology for a given imaging modality has been carried out. It has been highlighted that prostate segmentation techniques.

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