Anatomical Visions of Prostate Cancer in Different Modalities

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Abstract

Objectives: Prostate cancer (CaP) is the second utmost diagnosed cancer among aged men all over the world. CaP contributes as a main health issue for men, posing a challenge to oncologists, urologists, and radiologists for diagnosis purpose. **Methods**: There are several ways to delineate the prostate capsule using different imaging modalities, which act as one of the vital step for development of Computer Aided Diagnosis (CAD) system. **Findings**: In order to assist novice researchers for CaP diagnosis, this paper presents the general working theme of CAD system and highlights the different classes of existing prostate segmentation techniques. In order to study different cancerous or non-cancerous anatomical views of CaP in different modalities, the key role of this paper is to fill the gap between the actual CaP view and beginner perception about CaP Region of Interest (ROI). **Application/Improvement:** Various research gaps that are current open challenges for competent and effective development of Computer Aided Diagnosis (CAD) system for CaP are also a part of this paper.

Keywords: Cancer, CAD, Diagnosis, Modality, Prostate

1. Introduction

Prostate cancer (CaP) is drawing serious attention of an urologist and radiologist for early and accurate diagnosis because of exponential progression in the number of deaths among aged men globally¹. CaP also engrossed the attention of different medical imaging diagnostic researchers for developing distinguished Computer Aided Diagnosis (CAD) system for CaP which can assist the urologist or radiologist for curative timely decisions. In order to build a standard CAD system, appropriate vital steps, i.e. preprocessing, segmentation, feature detection, feature selection and feature classification are accomplished for a concerned modality. Region of Interest (ROI) i.e. segmented area plays a key role in the development of a CAD system as ROI is only the affected part of the body which needs diagnosis. The main outcome of a CAD system is to predict the benign or malignancy of ROI. Paper

organization is as follows. Section 1 highlights the need of accurate CaP ROI for the robust working of CAD system. Section 2 describes the general working theme of CAD system. Section 3 outlines the existing different classes of prostate segmentation approaches. Section 4 and 5 focus on the different anatomical views of CaP in Ultrasound and MRI images respectively. Section 6 states the existing challenges or gaps which are essential to be addressed for better development of CAD. Lastly, conclusion is presented in section 7.

2. Outline of CAD System

The clinical decisions of the radiologists have been aided with the development of CAD that comprises of Computer Aided Detection (CADe) and Computer Aided Diagnosis (CADx). A major advantage of CAD system is the lesion detection and distinction between malignant



Figure 1. Prostate CADx workflow.

and non-malignant tumors, which can be done efficiently to aid healthcare decisions. The different stages of CAD system are: preprocessing, segmentation, registration, feature detection, feature selection, feature classification. A CADx system for CaP detection takes multi-parametric MR images (MP-MRI), processes them, and generates a specific diagnostic result. The different stages of CAD system are shown in Figure 1. The pre-processing stage transforms the raw image to final image on which rest of the all stages of CAD system are fully dependent. This phase is very crucial because the appropriate choice of filters retains the most important image features which are mandatory required for perfect diagnosis. The variation of patient intensity values differs in the images in multiple scans. To address the inter-patient variability issue and make the signal intensity consistent, images are typically normalized. The standard T2WI images are mainly considered for the detection. T2WI has the more detailed anatomical structure of the prostate than other MR images. Different modalities of images when fused together, lead to better diagnosis of CaP region. Due to the patient movement and variation in image orientation during MRI scan, the translation and distortion of the prostate and neighboring organs are very common, which are corrected by registering the MRI sequences for feature extraction.

3. Prostate CADe

A numerous research has been carried out over the years for finding the solution determining the exact location, shape, texture of the prostate providing help in clinical decisions. Different modalities of imaging have been done for exact identification of the prostate. Some of the major contributions and methods have been detailed in this section. The segmentation method has been divided into different categories as contour and shape based, region-based, supervised and un-supervised classification approaches and hybrid techniques².

3.1 Contour and Shape based Segmentation

The contour and shape based approaches focuses on extraction of features and shape information of the prostate.

- a. Edge-based segmentation Different edge detection methods such as Prewitt, Sobel, Canny are popular because of their simplicity and less computational cost². However, these methods results in false edge detection or even broken edges due to the presence of noise. The expensive edge connecting algorithms are sometimes deployed for connecting the edges for obtaining pattern information for proper segmentation.
- b. Probabilistic filtering The Kalman filter and particle filters are probabilistic based filters that have been used for segmenting images. These techniques model the periphery of an organ resulting in fast and efficient results³.
- c. Deformable model based delineations -Deformable model is guided by internal and external energies where external energies disseminate deformable model in the direction of the object periphery and internal energies for preserving smoothness of delineations during deformation³⁻⁶ are some research in active shape model for deformable segmentation.

3.2 Region based Segmentation

- a. Atlas- Atlas is created through manual segmentation of anatomical structures registering to a common coordinate system frame. The atlas acts as reference frame for sectional images that finds a one-to-one transition mapping of the target image.
- b. Graph partition- In graph partition method collection of pixels together is considered as nodes while the edges among pixels nodes are considered as a cost. The graph is segregated by minimizing a cost function and group into different classes².

3.3 Supervised and Unsupervised classification based segmentation

The classification and clustering algorithms are deployed for assigning labels in supervised approach and grouping the similar region in unsupervised approach. Classifier based segmentation- The data in a training set are given a class-label. With the number of such objects training set is build to assign a new label for observed feature vector. Clustering based segmentation- Each data is related to a feature vector and the similar objects are grouped together based on the set of feature vectors determined by a distance measure.

3.4 Hybrid segmentation

The various methods are combined together to obtain better results for shape, feature and texture. The combined methods are robust to noise. Table 1 describes

Contour and shape	Techniques	Benefits	Shortcomings
	Edge	Easy to extract	Edges broken
	Shape	Robust against noise and artifacts	Strong edge information required for fitting
	Probabilistic filters	Vigorous against noise periphery	Challenging to initialize and extent to 3D
	Deformable model	Smooth contours Shape information preserved Extension to 3D	Depends on reliable edge information Rigid shape representation

 Table 1.
 Benefits and shortcomings of prostate segmentation methods

Table 1 Continued

Region	Atlas	Automatic Acquire prior shape and intensity information	Prone to registration errors Slow
	Graph partitioning	Competent optimization Region based information assimilated	Manual interaction required
Supervised Unsupervised	Classification	Robust against noise Automatic	Training is necessary No prior shape information required
	Clustering	Prior training not required Automatic	No prior shape information required
Hybrid		Robust to imaging artifacts, noise Produces good result	Combinations is difficult

various pros and cons of different prostate segmentation methodologies.

4. CaP in Ultrasound Images

Prostate Transrectal ultrasound (TRUS) investigation is the conventional procedure employed to achieve methodical fundamental operations of prostatic tissue for histological analysis. It is generally used to endorse and rate CaP in a patient with a prominent serum Prostate Specific Antigen (PSA) level or unusual Digital Rectal Examination (DRE) of the prostate. TRUS permits the demarcation of prostate gland anatomy in which two different regions can be recognized encompassing the interior gland (periurethral and Transition Zone (TZ) glandular tissue) and the exterior gland (Central Zone (CZ) and Peripheral Zone (PZ) glandular tissue). The exterior gland. The periphery among the two glands characterizes the surgical capsule of the prostate. The majority



Figure 2. Transabdominal ultrasound scan image reveal intravesical enlargement of the enlarged median lobe of the prostate.



Figure 3. Image reveals gross enlargement of the prostate mainly involving the transition zone.



Figure 5. Image reveals few small cysts in inner gland.



Figure 4. Image exposes intra-vesical enlargement of median lobe.



Figure 6. Transrectal Ultrasonography CaP images with a hypertrophied transition zone (yellow arrows) and a compressed peripheral zone (blue arrows).



Figure 7. TRUS image reveal large hypoechoic area along the left peripheral zone, suggestive of carcinoma.



Figure 9. A large hypoechoic region in the left peripheral zone indicative of CaP.



Figure 8. Sagittal image of the prostate.



Figure 10. Axial prostate image.



Figure 11. Sagittal image of a prostate. White arrows show darkly hypoechoic regions indicative of periprostatic veins.



Figure 13. 3-D ultrasound images of prostate calculus and adjoining part of the bladder.



Figure 12. Sagittal image of the prostate. White arrows indicate calcification in the prostatic urethra.



Figure 14. Image reveals small calculus of lodged in the prostatic urethra.



Figure 15. Image illustrates internal surface of the urinary bladder.

of CaP arises in the outer gland and variations of benign prostatic hyperplasia (BPH) are limited to the interior gland. Figure 2 to Figure16 demonstrates different anatomical views of CaP in ultrasound images.

4.1 CaP in Magnetic Resonance Images

Prostate zonal anatomy is best revealed with MRI. In T2w series, the healthy prostate can be alienated into the PZ, which shows high signal intensity due to its high water content, and the central gland (comprising CZ and TZ) has lower signal intensity Figure 21. CaP is commonly realized as the region of low signal abnormality in the PZ. Some CaP's are so intense and cannot be seen on standard MRI. Other disorders, such as prostatitis, atrophy and calcifications, may also cause low signal intensity and result in a number of false positives. MRI is valuable in the local cancer staging and treatment planning. MRI is gold standard for patients who are at intermediary or high



Figure 16. Image reveals a detailed prostate region.



Figure 17. MRI Image illustrates the coronal prostate region with no spread to lymph nodes.



Figure 18. MRI Image reveals the axial prostate region with no spread to lymph nodes.



Figure 20. MRI Image illustrates the axial prostate region spread less than half of one lobe with no spread to lymph nodes.



Figure 19. MRI Image illustrates the coronal prostate region having tumor invades the seminal vesicles, spread beyond local nodes.



Figure 21. MRI image reveals spread outside the prostate.



Figure 22. Coronal T2-w MRI imaging of normal prostate region.



Figure 24. Axial T2-w imaging of CaP of the left peripheral zone with an inflammation of the capsule signifying early extracapsular takeover (arrow).



Figure 23. Axial T2-w imaging of CaP of the right peripheral zone seems as a low signal area (arrow).



Figure 25. Axial T2-w imaging of CaP at the right base with extension into the periprostatic fat (arrow).



Figure 26. Coronal T2-w imaging of CaP of the prostate base with capture of the seminal vesicles (arrow).

risk of localized disease advancement and who are being scrutinized for radical treatment (surgical prostatectomy or brachytherapy). Figure 17 to Figure 26 demonstrates different anatomical views of CaP in MR images⁸.

5. Research Gaps and Challenges

The critical⁹ illustrates the problems with the conventional methodologies highlighting the area that needs to be focused on achieving better accuracy in results. Prostate delineation is still an open issue with a multimodal image fusion of at least two different imaging modalities which will surely add new valued direction for diagnosis of CaP. To avoid under or over segmentation, there is a need of integration of the prostate, rectum, bladder and the seminal vesicles structures into the segmentation algorithms. There is need of segmentation and classification of related prostatic structures or substructures i.e. segmentation of the prostatic zones (transition, central and peripheral). Prior information about texture and shape must be incorporated in the algorithms for determining the exact boundaries. A fully-automatic segmentation algorithm needs to be developed that realized with the use of machine learning techniques for estimation of the location of the prostate. There is need of testing multi-parametric MRI on a single segmentation framework. Existing studies lack in testing on dataset of both 1.5 Tesla and 3.0 Tesla scanners which may develop more generic algorithms. Quantitative comparison of different existing approaches on single/multiple benchmark dataset needs detailed investigations. Lack of inclusion of all pre-processing steps in the current CAD workflow demands the evaluation of results by incorporating all pre-processing steps which could improve the results. Absence of consistent metrics in the assessment of delineation outcomes makes the valuation of developed approaches difficult. Another important requirement is the volume measurement of a prostate. The image must be captured from different orientation and view to make the clinical decisions easier and more accurate.

6. Conclusion

This paper at large described the general scheme of a CAD system and various existing approaches of prostate segmentation. Different anatomical views of CaP are also presented for novice researchers to learn the actual view of cancer in different modalities. Author stated various research gaps and challenges which will motivate the active researchers to address the same in order to support the urologist or radiologist for early diagnosis and ultimately lead to increased lifespan of Cap patients.

7. References

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