Detection of Prostate Cancer with MAPS Feature Model using Region Growing Algorithm

V. Parvathavarthini, S. M. Ramesh, M. Irshad Ahamed

Abstract: ***In this paper we present a new method for automated and quantitative grading of prostate cancer. A total of 102 graph-based, morphological, and textural features are extracted from each tissue patch in order to quantify the arrangement of structures within digitized images of prostate cancer. A support vector machine (SVM) is used to classify the prostate into benign or malignant based on four appearance features extracted from registered images. Moreover, in this paper we introduce a new approach to generate level of cancer, that illustrate the propagation of diffusion in prostate tissues based on the analysis of the MAPS of the change of the gray level values of prostate voxel using (GGMRF) image model. Finally, the tumor boundaries are determined using a level set deformable model controlled by the diffusion information and the spatial interactions between the prostate voxels. Experimental results on 28 clinical diffusion weighted MRI data sets yield promising results.***

Keywords: classifiers; C Timages; MAPS; Prostate cancer.

I. INTRODUCTION

Prostate cancer is the most frequently diagnosed in the American male population and the second leading cause of cancer death. Latest prostate cancer studies reported an estimated 241,740 new cases and a mortality rate of close to 28,170 in 2012 [1]. Fortunately, the survival rate is very high for patients with an early diagnosis. The techniques currently used for diagnosing prostate cancer are clearly unsatisfactory. For example, Prostate Specific Antigen (PSA) screening doesn't offer accurate information about the location and extent of the lesion(s). In addition, PSA is associated with a high risk of over diagnosis of prostate cancer. On the other hand, imaging tests using different imaging modalities (e.g., Transrectal Ultrasound (TRUS), computed tomography(CT), MR Spectroscopy (MRS), Dynamic Contrast Enhanced MRI(DCE-MRl), and diffusion-weighted MRl (DWI) have been recently exploited to develop non-invasive Computer-Aided Diagnosis (CAD) systems for the early detection and diagnosis of prostate cancer. MRI modalities have been shown to increase the accuracyof diagnosis and enable more efficient treatment. Becausethe development of prostate cancer is associated with changes inmetabolism, diffusion,

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And blood flow, magnetic resonance (MR) imaging techniques can aid in the detection and evaluation of thedisease. Diffusion-weighted imaging has the distinct advantage ofbeing acquired very rapidly, without the use of intravenous contrastmaterial or specialized hardware. This paper focuses on DWI sincethey have shown more capabilities in determining the size and theshape of the prostate gland and localizing the cancer foci.Diffusion-weighted MR imaging has been clinically applied inseveral organs. Not only is it used to show the affected tissue aftera stroke, but also it can differentiate brain tumors [2] or vertebralmetastases in, for example, prostate cancer [2]. The diffusion datacan be presented as a signal intensity or as an image map of the apparentdiffusion coefficient B (ADC) [3]. In DWI, the image contrastis determined by the random microscopic motion of water protons,that is, the brownian motion. The diffusion can be measured in vivoby using the MRl because of its sensitivity to motion. This sensitivityto motion can be increased by the addition of strong magneticfield gradient pulses (b-values) to the pulse sequence. The first study to apply a strong magnetic field to DWI prostate images was performed by Shimofusa et al. [3] with a high b-value (b= 1000s/mm2). Their study did not use an endorectal coil. However, the sensitivity as well as specificity was higher than in other former studies with an endorectal coil [4, 5]. Since then, several prostatic MR imaging studies [6, 7] have investigated the detection ability of cancerous tissue using DWI images. The majority of these studies requires user interaction to select a ROI around the prostate, and therefore biases the final decision and brings up the issue of underestimating the problem in the entire graft, just as with biopsy. To overcome this limitation, we propose a new non-invasive image based CAD system for the early diagnosis of prostate cancer using DWI.

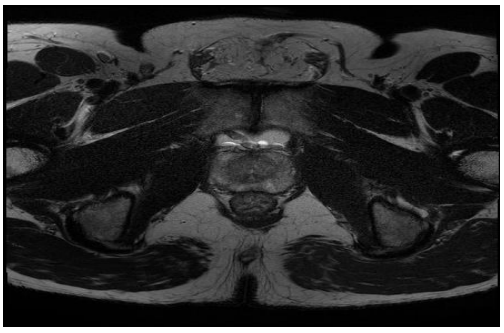


Fig. 1: Example multiparametric MRI slices of the same prostate gland, using T2w and diffusion-weighted imaging (DWI). Each modality provides different information about the prostate gland to aid in the clinical decision support process.

II. LITERATURE SURVEY

In [8] Region growing algorithm proposed for segmentation of CT scan images of the Prostate. This algorithm starts with a seed pixel and also checks other pixels that surround it. It determines the most similar one and, if it meets certain criteria, it will include in the region. The region is developed by examining all unallocated neighboring pixels to the region.

In [9] proposed an approach for detection of cancer cells from Prostate CT scan images. This work presents a method to detect the cancer cells from the CT scan image. It reduces the error in the detection part made by the doctors for medical study. It is based on Sobel edge detection and label matrix. Sobel operator helps to locate the edges in an image. It does so by finding the image gradient. Image gradient gives the change in the intensity of the image. Also in [10] a system using Computer Aided Diagnosis (CAD) for finding the edges from CT scan images of proatate for detection of diseases is used. Thresholding algorithm [11] gives filtering to detect the sputum cell from the raw image for early detection. A novel method, watershed transformation is presented for image segmentation in [12]. Morphological operations which are opening and closing operations are used to process the gradient image. It is used to eliminate the over segmented area and to reconstruct the morphological gradient which can maintain the shape of gradient image.

The main idea of this paper is to detect the tumour and decide whether it is cancerous or not. It also finds the prostate cancer stage and gives more accurate result by using different techniques.

III. MORPHOLOGICAL MODEL

In the proposed method, initial identification of candidate tumor regions is automatically performed using multiparametric MRI and morphology. After candidate regions are identified by the automatic tumor candidate identification algorithm, textural and morphological features are extracted to form a hybrid morphological-textural feature model that combines high-level morphological features with low-level textural features.

3.1. Automatic Tumor Candidate Identification

In the proposed system using guidelines for clinical multiparametric MRI prostate cancer screening by a radiologist [13] to identified automatically. Tissues satisfies these criteria were grouped into connected regions and analyzed morphological feature model. In particular, diffusion characteristics and morphology were used to automatically identify candidate regions in the proposed system.

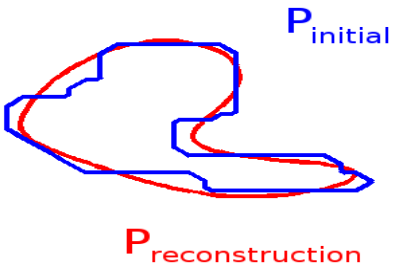
3.2. Textural Features

After the tumor candidate regions have been identified, a set of low-level texture features were computed for those regions as part of the proposed hybrid morphological-texture feature model. Texture features were included to capture the different textural characteristics between cancerous and healthy tissue [11]. T2w intensity values were included as an initial feature. In addition, a series of local statistical features and Gabor filter responses were extracted from the T2w intensity images in order to quantify textural characteristics of imaged tissue [11]. Texture features were also computed using ADC values and likewise augmented with the ADC map as a further feature. Feature values for each region were obtained by averaging textural filter responses over the region. The statistical features consisted of the median, standard deviation, and average deviation first-order features as well as the contrast, correlation, and homogeneity second-order features. All were computed using 3 _ 3 and 5 _ 5 voxel regions around the voxel of interest [11]. Gabor filters were applied at a combination of scales and orientations totalling 18 features, corresponding to the scales u0 = $\{16\sqrt{2}; 32\sqrt{2}; 64\sqrt{2}\}$ and the orientations $\theta = n\pi/6$; n = 0….6.

3.3. Morphological Features

In the proposed morphological feature model, a set of high-level features are also computed to characterize the morphology of the tumor candidate region. Morphological features capture structural information about a candidate region by applying operations which smooth the shape of the region boundary. Regions with little morphological irregularity undergo little change with the smoothing operator, while regions with highly irregular shapes will see a drastic difference.

(a) Morphological Area Feature



(b) Morphological Perimeter Feature

Fig. 2: Illustrations of the morphological features.

In 2a, the area feature illustration, purple and orange contours denote the morphological opening and closing, respectively, of a candidate region. The large difference in areas between the\ contours results in a high feature value for this region.

In 2b, the perimeter feature illustration, a candidate region contour, shown in blue, has a perimeter similar in length to that of the region's low-frequency Fourier reconstruction, shown in red, resulting in a low feature value for this region

The first feature in this group is the normalized difference in area between the morphological closing of the region and the morphological opening of the region, using an identical disk structuring element for both operations [15]

$$f1^B = \frac{A\ closed - A\ opened}{A\ initial} \qquad (1)$$

A denotes the area of a region. Peaks and valleys in the border of the region will cause the area to increase after closing, while it will decrease after opening (i.e., Aclosed≥Aopened); therefore, regions with very irregular borders will have a greater difference between these two values, and the feature value will be greater. Smaller feature values then correspond to regions with borders which do not feature sharp peaks and valleys. An example region is shown in fig. 2a.

The second morphological feature compares the length of the region's perimeter before and after eliminating highfrequency components in the Fourier space, and normalizing the difference:

$$f2^B = \frac{|P\ initial - P\ reconstruction|}{P\ initial} \qquad (2)$$

where each P is the perimeter of the region denoted by its subscript. Since high-frequency components capture rapid changes in the shape of the region, this feature will be greater for regions with rapidly-varying boundaries than for those

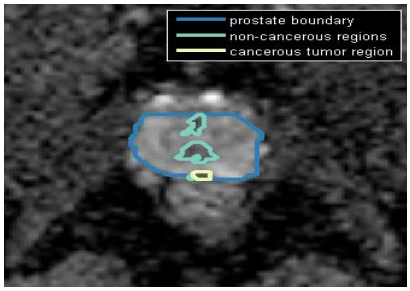


Fig. 3: An example patient case with contours for the prostate gland (blue), non-cancerous regions (green), and cancerous tumor region (yellow) overlaid on the apparent diffusion coefficient (ADC) map of the prostate gland. Note that the yellow and green regions exhibit similar ADC values, indicating that ADC alone is insufficient for delineation between cancerous tumors and non-cancerous regions. with smooth, slowly-varying boundaries [13]. An example region is shown in Fig. 2b.

3.4. Region Growing

Region growing is an interactive segmentation methodwhich requires some seed points to be initialized andstart the process. This technique separates a region ofimages based on some predefined law according tointensity information. In the simplest form, regiongrowing requires one seed point and the region will be grown based on its homogeneity properties accordingto neighbouring pixels [16]. There are some region-based methods which have differences in homogeneity criterion definition. A general region algorithm for extracting one object is as given below:

Algorithm: Input (seed point)

(1) Region r ¼ {seed}
(2) While r.neighbours 6¼
(a) For each voxel x in r.neighbours, if P(x,r) ¼ true,then add x to r
(b) End while
(3) Return r

In the above algorithm, r is a region that we want to extract. Based on homogeneity criteria, some regiongrowing- based methods have been presented. In this algorithm, the fundamental region-growing method has been explained by evaluating the distance between voxel x and the mean of region which is presented by the function P [42_44]. P is expressed as

Pðx; rÞ ¼ jfðxÞ _ mrj< T; ð10Þ

wheremr is the region's mean of r and T is a threshold. The threshold can be selected manually or using an automated method. Region growing has been applied on the CT image of the prostate gland. In this figure, two seed points have been selected from two different regions and the region-growing process has been applied. The disadvantage of region growing is that the result of this technique significantly depends on the seed point selection. Selecting a seed point depends on human ability; thus, the extracted shape considerably thresholding. depends on the user. Although noise sensitivity in this method is less than thresholding, but it can make a hole in the extracted shape or produce a disconnectedarea . Region growing has been widely used in mammograms in order to extract the potential lesion from its background [17].

IV. EXPERIMENTAL RESULT

Region labels were used as ground truth to train SVM classifiers in a leave-one-out cross-validation scheme. Each region was held out while the remaining regions were used to train a classifier, which was then used to predict the held-out region's label. Classification performance was assessed by evaluating the accuracy, sensitivity, and specificity of these predictions.

4.1. Feature Model Performance

The performance of each feature set on the training and classification process described above are shown in Figure 4.

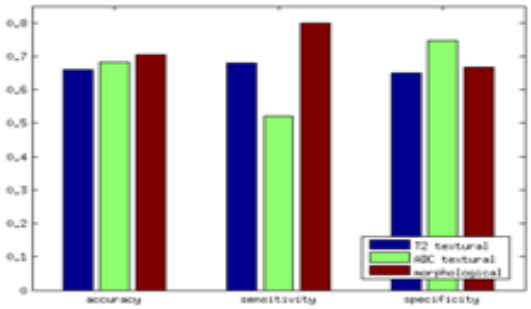


Fig. 4: Classification performance (accuracy, sensitivity, and specificity) of textural and morphological features separately.

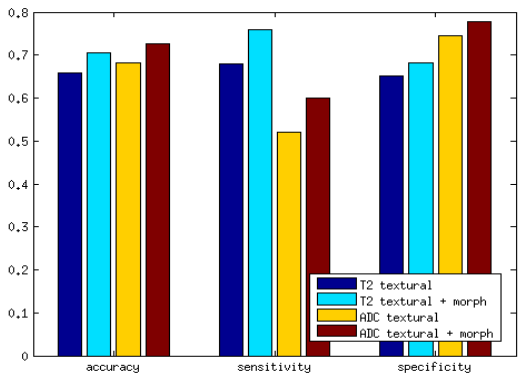


Figure 5: Classification performance (accuracy, sensitivity, and specificity) of textural features augmented with morphological features

In addition to the T2w-based textural features, a set of similar texture features was compute using ADC intensity values. Although the ADC-based textural features achieve slightly higher accuracy compared to the T2w textural features, they suffer from a drastic loss in sensitivity. The benefit of adding high-level morphological features to construct morphological feature models is clear.

V.CONCLUSION

A morphological feature model was proposed, which departs from current methods by combining the use of CT images with low-level textural and high-level morphological properties. This morphological-textural feature model appears to offer improved diagnostic power compared to using texture features alone, as well as being easier to interpret by radiologists.

5.1. Recommendations and Future Work

As these results are preliminary, further validation with larger datasets is warranted. At this point, false positives and false negatives should be carefully examined in the feature space to determine if additional intuitive features might reduce misclassifications. As well, user acceptance testing in a clinical environment is needed to ensure the intuitive features correspond with the perception of expert diagnosticians, and could be used to inform the design of new intuitive features..

REFERENCE

1. American Cancer Society, "Cancer Facts and Figures 2012"
2. T. Hacklander, C. Scharwachter, R. Golz, and H. Mertens, "Value of diffusion-weighted imaging for diagnosing vertebral metastases due to prostate cancer in comparison to other primary tumors," RoFo, vol. 178, no. 4, pp. 416-424, 2006
3. R. Shimofusa, H. Fujimoto, H. Akamata et aI., "Diffusion weighted imaging of prostate cancer," 1. of Comp. Assi. Tomography, vol. 29, no. 2, pp. 149-153, 2005.
4. K. K. Yu and H. Hricak, "Imaging prostate cancer", Radiologic vol. 38, no. 1, pp. 59-85, 2000.
5. S. Ikonen, P. Karkkainen, L. Kivisaari et aI., "Endorectal magnetic resonance imaging of prostatic cancer: comparison between fat-suppressed T2-weighted fast spin echo and threedimensional dual-echo, steady-state sequences," Eur. Radiology, vol. 11, no. 2, pp. 236-241, 2001.
6. T Tamada,TSone,Y Jo, et al. "Prostate cancer: relationships between postbiopsy hemorrhage and tumor detectability at MR diagnosis." Radiology, vol. 248. pp. 531-539, 2008.
7. K Yoshirnitsu, K Kiyoshima, H lrie, et al. "Usefulness of apparent diffusion coefficient map in diagnosing prostate carcinoma: correlation with stepwise histopathology," I MagnReson Imaging, vol. 27, pp.132-141, 2008.
8. NihadMesanovic, HarisHuseinagic, Matija Males, ,MislavGrgic, Emir Skejic, MuamerSmajlovic "Automatic CT Image Segmentation of the Lungs with Region Growing Algorithm"
9. SayaniNandy, Nikita Pandey " A Novel Approach of Cancerous Cells Detection from Lungs CT Scan Images'' International Journal of Advanced Research in Computer Science and Software Engineering Volume 2, Issue 8, August 2012
10. Prof. Samir Kumar Bandyopadhyay "Edge Detection From Ct Images Of Lung'' International Journal Of Engineering Science & Advanced Technology Volume - 2, Issue - 1, 34 – 37
11. FatmTaher, NaoufelWerghi and Hussain Al-Ahmad "Extraction of Sputum Cells using Thresholding Techniques for Lung Cancer Detection" 2012 International Conference on Innovations in Information Technology QinghuaJi,Ronggang Shi "A Noval Method of Image Segmentation Using Watershed Transformation"2011
12. International Conference on Computer Science and Network Technology
13. M. A. Haider, T. H. van der Kwast, J. Tanguay, A. J. Evans, A.-T. Hashmi, G. Lockwood, and J. Trachtenberg, "Combined T2-weighted and diffusion-weighted MRI for localization of prostate cancer." AJR. American journal of roentgenology, vol. 189, no. 2, pp. 323–8, Aug. 2007
14. Madabhushi, M. D. Feldman, D. N. Metaxas, J. Tomaszeweski, and D. Chute, "Automated detection of prostatic adenocarcinoma from high-resolution ex vivo MRI." IEEE transactions on medical imaging, vol. 24, no. 12, pp. 1611–25, Dec. 2005.
15. R. Amelard, A. Wong, and D. A. Clausi, "Extracting Enhancing Skin Lesion Classification," in 34th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, San Diego, 2012, pp. 4458 – 4461.
16. D. L. Pham, C. Xu, and J. L. Prince, "A survey of current methods in medical image segmentation," Ann. Rev. Biomed. Eng.,Vol. 2, pp. 315_37, 1998.
17. Olivera, J. Jordi Freixeneta, and J. Joan Mart_ia, "A review of automatic mass detection and segmentation in mammographic images," Med. Image Anal., Vol. 14, no. 2, pp. 87_110, 2010.

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