Detection of Prostate Cancer Using Radial/Axial Scanning of 2D Trans-rectal Ultrasound Images

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ABSTRACT

The search for improvement in the result of segmentation of regions of interest in medical images has continued to be a source of challenge to researchers. Several research efforts have gone in to delineate regions of interest in the prostate gland from Trans-rectal ultrasound (TRUS) 2D-images. In this work, we develop a fast algorithm based on radial/axial scanning of the pixels of the prostate gland image with the goal of detecting hyper-echoic pixels that are bound within the boundaries of the gland TRUS 2D-images. The algorithm implements expert knowledge and utilizes the features extracted from the intensity of the TRUS images, primarily the relative intensity and gradient to delineate region of interest. It employs radial/axial scanning of the image from common seed point automatically selected to detect the region of the gland and subsequently hyper-echoic pixels which indicate suspected cancerous tissue cites. Evaluation of the algorithm performance was done by comparing detection result with that of expert radiologists. The detection algorithm gave an average accuracy of 88.55% and sensitivity of 71.65%.

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1. INTRODUCTION

Prostate cancer has become a pandemic. Prostate cancer is the most frequently diagnosed cancer in men aside from skin cancer, and 180,890 new cases of prostate cancer have been expected in the US during 2016 [1]-[3]. As a widespread but less aggressive cancer, the early diagnosis of prostate cancer is critically important for treatment of this disease. Treatment is available, but it is most successful when the cancer is in early stage. For detection of cancer in early stages, it is important for men over the age of 50 to go for an annual screening [4]. The computerization of medical image segmentation plays an important role in medical imaging applications. Its application is in different areas such as diagnosis, localization of pathology, study of anatomical structure, treatment planning, and computer-integrated surgery [5]. The variability and complexity of the anatomical structures in the human body, however, have resulted in medical image segmentation remaining a hard problem [6]. Over the last few years of intellectual discourse and research, the problem of prostate segmentation, delineating boundaries and volumes, has received considerable attention [7]-[9]. Different segmentation techniques have been applied by different researchers. Among these techniques include edge-detection, graph-searching, deformable models, geodesic active contours, thresholding, classification, clustering, region growing, split and merge, atlas-guided, artificial neural network, and watershed. Ladak et al [10] developed a method based on a deformable contour model, named the discrete dynamic contour (DDC) [11]. In this method, initialization requires the user to select only four (4) points from which the outline of the prostate is estimated by cubic interpolation functions and shape information. However, the success of their approach is dependent on the careful initialization of the contour, which requires the user to select points on the prostate boundary.

Yang et al. [12] presented an automatic segmentation algorithm that uses atlas registration with statistical priors on texture of image. Patient-specific Gabor features from the atlas database was used to train kernel support vector machines (KSVMs) [13]. In different work, Zhan et al. [14] proposed the use of a deformable for automatic segmentation of prostate from trans-rectal ultrasound (TRUS) images by statistical matching of both shape and texture. They applied a set of Gabor-support vector machines (G-SVM) on different patches of model surface. The G-SVM was then trained to adaptively capture texture priors of TRUS images for defining tissues as a prostate or non-prostate in different zones around prostate boundary. Akbari et al. [15] developed an algorithm which used statistical shape, texture information and intensity profiles. A set of wavelet support vector machines (W-SVMs) was applied to images at various sub-regions of the prostate gland. Finally the intensity profiles were used to improve the segmentation result based on the boundary detection. Award [16] proposed a technique that used expert knowledge and gradient vector flow (GVF) deformable contour to both segment the prostate boundary and detect suspected cancerous regions within the prostate gland.

These previous works used techniques that require a lot of computation time and training data. Support vector machines and its variants have a disadvantage of long run time to achieved needed convergence. For detection of specific regions of interest will require even more computation time using these previous techniques, hence the need for a fast and robust method. The new technique collaborates with the propositions of Wu et al. [17] and Eskandari et al. [18] for delineating prostate gland while implementing experts' knowledge and radial scanning of pixels features to detect suspected cancerous tissues. The new algorithm emphasizes detection of hyper-echoic pixels within the region of the prostate gland so delineated. Consequently the gland image was divided into sixteen (16) sections fewer than in [18]. This is because of the following expert knowledge that was implemented: * Cancerous cells are not scattered, but occur in clusters. * Cancer is not likely to occur along the edges of the gland; rather they occur within the gland zones [16], [19]. The result of the fewer sections is reduced processing time giving rise to fast detection algorithm. From experiments the pixels intensity ranges that represent hyper-echoic intensity are 0 to 55 for dark images and 0 to 50 for light images (on a grayscale image intensity range of 0 to 255).

2. RESEARCH METHOD

2.1 Method of Detecting Suspected Cancerous Tissues of Prostate Gland Region

In order to automatically extract the prostate gland and detect suspected cancerous cites or tissues from trans-rectal ultrasound 2D-images, a four stage algorithm shown in Figure 1 is described. The first stage of the proposed segmentation algorithm is preparing the image by enhancement using sequential sticks algorithm [16], [20]. This stage ensures reduction of noise especially speckle noise which affect TRUS images. The second stage uses segmentation algorithm described in [18] to build and store the coordinates of the boundary of the prostate gland as well as a centre point. The third stage detects the hyper-echoic pixels within the stored boundaries of the prostate gland using some prior and expert knowledge. This stage comprised of two sections. First it processes each of the sector (scanning along the radii/axes) boundaries for pixels within it and stores their properties in sector line boundary coordinates table and then it checks the table for hyper-echoic properties applying the prior knowledge. The last stage is displaying the hyper-echoic pixels within the image of the prostate gland.

By definition [16], segmentation problem is the union of all sets within the segmented region. Therefore the result of this segmentation will be two sets of regions, namely R_1, region of the prostate gland (content of all sector line boundary coordinates table) and R_2, region of tissues suspected to be cancerous (content of table of hyper-echoic pixels coordinates). Therefore we have Equation 1;

$$F=\bigcup_{k=1}^{2} R_k \tag{1}$$

where F, the segment of the prostate gland in the image, is the union of two sets of regions R_1 and R_2. R_1 is the region of the gland that has no pixels suspected to be cancerous while R_2 is the region of the gland where pixels have been marked as suspected cancerous cells. It is such that $(R_1 \cap R_2.)=\phi$. That is the two regions do not intersect, producing a null set, ϕ.

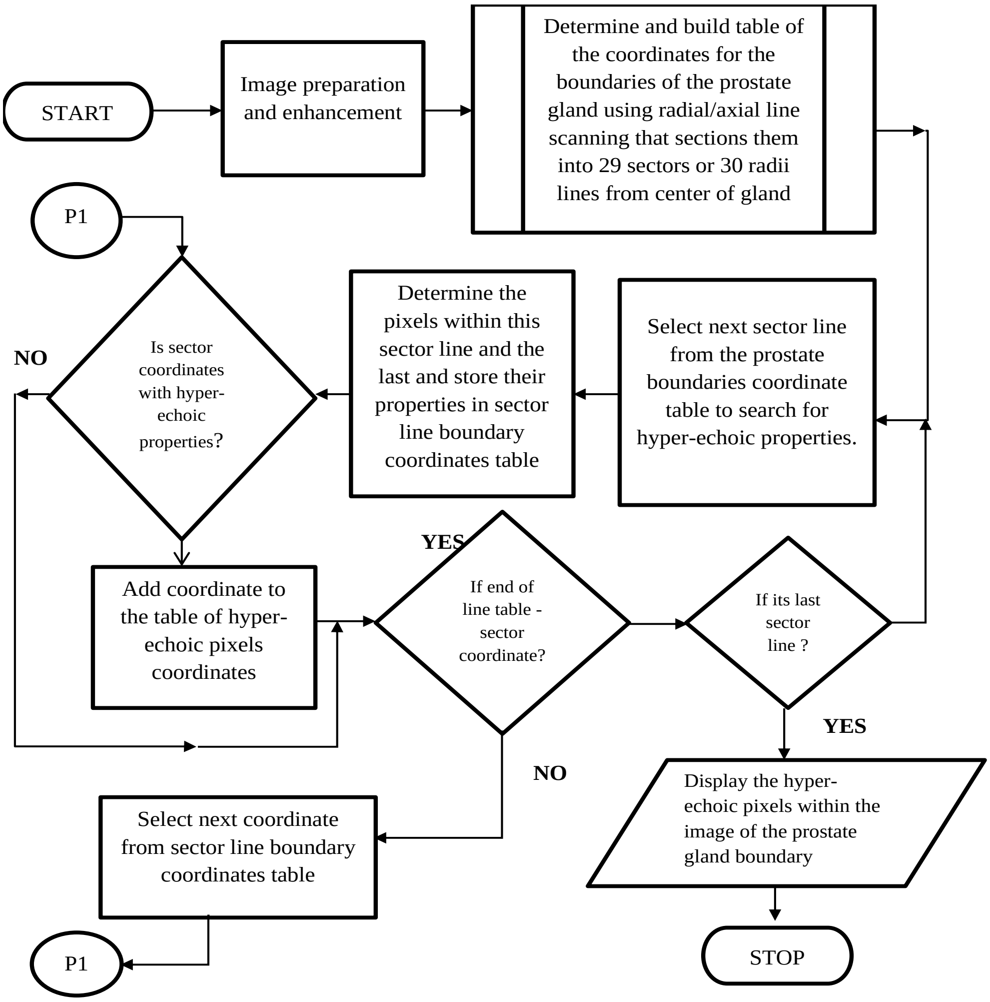


Figure 1. Flowchart of prostate cancer detection algorithm

2.2 Method of Evaluating the Result of Proposed Algorithm

The evaluation of the proposed algorithm uses area-based metrics. The area of an image or a region in the image is given by the total number of pixels comprising the image or the bound region of interest in the image [21]. The area of segment or region by the algorithm, A_s, is compared with the area of same segment or region by an expert, A_m. The parameters of sensitivity and accuracy are determined for each image sample. Average values for these parameters are determined for the algorithm performance. The area-based metrics procedure is as follows [11]:

a. Determine the area inside the expert manual contour, A_m. (To be determined by number of pixels inside the prostate gland contour as marked by the expert).
b. Determine the area inside the proposed algorithm contour, A_s. (To be determined by number of pixels inside the prostate gland contour by the proposed algorithm)
c. True Positive area, TP which is defined by the common area between both the expert manual and the proposed algorithm contours.

$$TP=A_s.(EX\text{-}NOR).\ A_m \tag{2}$$

d. False Positive area, FP which is equal to the area inside the proposed algorithm contour but outside the expert manual contour.

$$FP=A_s-TP \tag{3}$$

e. False Negative area, FN which is represented by the area inside the expert manual contour but outside the proposed algorithm contour.

$$FN=A_m-TP \quad (4)$$

f. **Sensitivity, S**, which measures the accuracy of a marking method to identify all marked pixels/regions;

$$\mathbf{S}=TP/A_m*100 \quad (5)$$

g. **Accuracy, A**, which measures the ratio between the pixels/regions which are correctly identified to the total number of pixels/regions;

$$A=\{1-(FP+FN)/A_m\}*100 \quad (6)$$

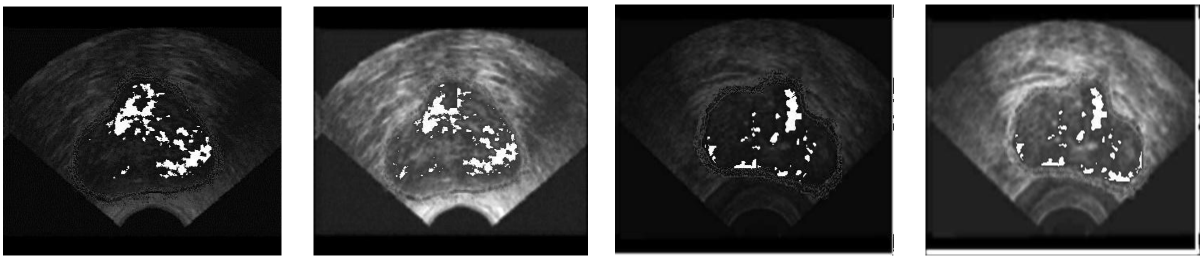
The codes for the algorithms were developed using MATLAB programming language. The implementation requires MATLAB version 7.5 or higher versions running on WINDOWS 7 or higher versions. The algorithms were tested with image samples obtained from an earlier work by Award [16]. Figure 2 shows some samples of original TRUS 2D-images.

Figure 2. Samples of original TRUS 2D-images of the prostate gland

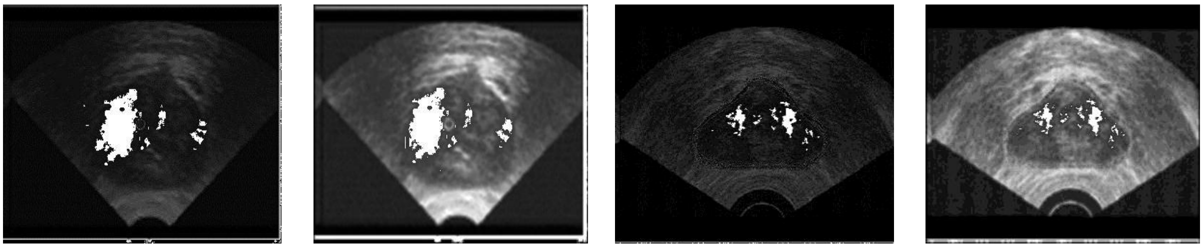
3. RESULTS AND ANALYSIS

The new algorithm was tested with TRUS 2D image samples of patients who have initial symptoms indicating evidence of prostate cancer at various stages. The result of detections by the new algorithm performed on some of the image samples are as shown in Figure 3 (a) to (f). The same image samples were presented to expert radiologists to mark sites in the image suspected to be cancerous and the result obtained were shown in Figure 3 (g) to (l). The two detection results have been presented side by side for comparison. The white sections within the prostate boundary show the suspected sites identified by both algorithm and expert.

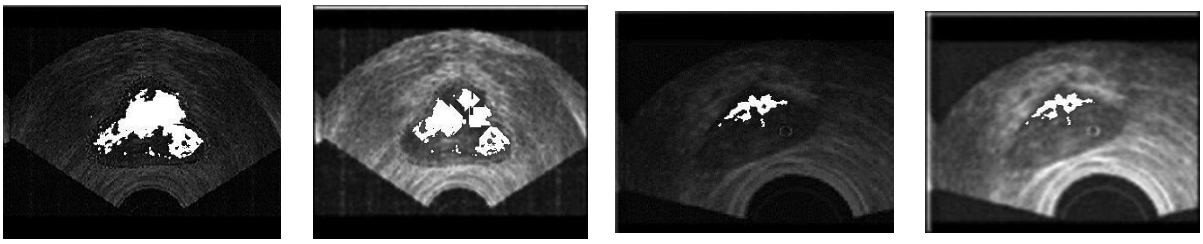
The results of the new algorithm were evaluated using the area-based metrics outlined in equations (2) to (6). The parameters of sensitivity and accuracy were determined for each image sample. Average values for these parameters are determined to measure the performance of the new algorithm. Table 1 shows the comparison of the accuracy and sensitivity values computed for 20 images. The average value was determined as well the standard deviation for the sample results. From the summary result obtained in the table, the algorithm achieved Accuracy of 84.17%, and Sensitivity of 78.49% with standard deviation of 13.84 and 13.68 respectively. The new algorithm is simple and does not involve complex and cumbersome computations. The algorithm executes fast and has performance that is highly comparable to existing ones. However, the algorithm fails to detect gland boundaries where there are tissues that show distinct higher intensities like tissues outside the gland region. This accounts for the low sensitivity value and high standard deviation recorded.



(a) Image 1–Algorithm detected (g) Image 1–Expert detected (d) Image 4-Algorithm detected (j) Image 4-Expert detected



(b) Image 2-Algorithm detected (h) Image 2-Expert detected (e) Image 5-Algorithm detected (k) Image 5-Expert detected



(c) Image 3-Algorithm detected (i) Image 3-Expert detected (f) Image 6-Algorithm detected (l) Image 6-Expert detected

Figure 3. TRUS 2D prostate images samples a) to f) with detected suspected cancer sites marked by new algorithm and g) to l) with detected suspected cancer sites in same samples marked by expert radiologist

Table 1. Comparisons of Cancer Detection Results

SAMPLE NO.	ACCURACY	SENSITIVITY
1	79.16	78.67
2	75.27	67.83
3	52.61	51.04
4	97.65	88.75
5	79.70	79.70
6	96.65	84.07
7	87.23	86.21
8	97.45	98.10
9	98.23	97.66
10	68.07	63.53
11	74.33	72.75
12	79.68	76.21
13	83.72	71.22
14	97.44	69.44
15	98.65	88.98
16	96.76	97.07
17	95.87	95.44
18	70.86	65.48
19	61.86	57.85
20	92.26	79.84

Average Values=84.17 78.49
Standard Deviation=13.04 13.04

The accuracy value of 84.17% implies that for every detection result by the algorithm one was about 80% certain (almost certainly true) that the patient with the prostate gland image was likely to have cancer cells in the regions identified. It was also interpreted to mean that the result obtained by the system at any given time for any image sample was almost certainly true.

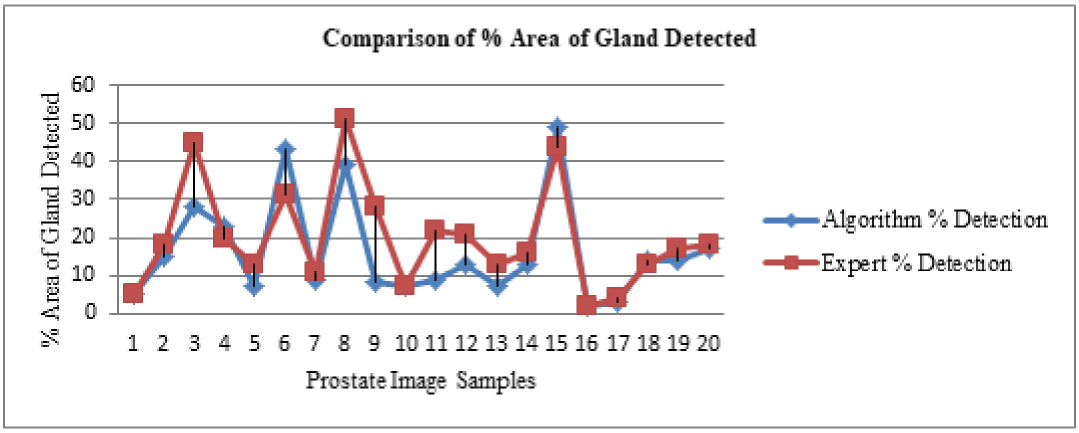


Figure 4. Comparison of the % area of gland detected by algorithm and expert

The percentage area of the prostate gland detected as suspected to be cancerous by both algorithm and expert were recorded for same image samples. The result for 20 samples is as shown in Table 2. The values obtained have been plotted for the purposes of comparison in the graph shown in Figure 4. The comparison shows that the detection for the algorithm and the experts were almost same for about 50% of the samples. There were remarkably variation in about 30% of the samples and slight variation in the remaining 20% of the samples. The graph generally reveals that the algorithm detection of suspected cancerous gland region closely agrees with expert opinion.

Table 2. Comparison of % Area of Gland Detected

SAMPLE NO.	% Area of Gland Detected by Expert	% Area of Gland Detected by Algorithm
1	5.03	4.91
2	17.71	14.60
3	44.55	27.98
4	20.04	23.13
5	13.26	6.44
6	30.55	43.30
7	10.95	8.73
8	51.11	38.04
9	27.48	7.93
10	7.23	6.39
11	21.77	8.88
12	20.52	12.72
13	12.44	6.78
14	15.98	12.92
15	43.8	49.06
16	2.35	2.37
17	3.44	2.91
18	13.35	13.61
19	16.52	14.03
20	18.33	16.58

The performance of the new algorithm on detection of cells suspected to be cancerous (hyperechoic pixels) compared with that proposed by Awad (2007) was summarized in Table 3. The table shows that the new algorithm gives higher accuracy than that proposed by Awad (2007) while the later produced lower standard deviation. Also the new algorithm yielded higher sensitivity with slightly lower standard deviation than that of Awad (2007). The new algorithm therefore yields better result in detection of suspected cancerous cells or hyperechoic pixels.

Table 3. Comparison of the Performance of New Algorithm with that Proposed by Awad (2007)

	New Algorithm		Awad's Algorithm	
Measures	Average	Standard Deviation	Average	Standard Deviation
Accuracy	84.17	13.84	84.16	6.46
Sensitivity	78.49	13.68	66.56	14.65

4. CONCLUSION

In this work radial/axial scanning with prior knowledge on image features were employed to both detect the prostate gland and subsequently the suspected cancerous tissues, hyper-echoic pixels, from an ultrasound 2D- image sample of the prostate gland. The new algorithm was tested with the same images used by the algorithm earlier proposed by Awad (2007). The resulting algorithm achieved high accuracy and sensitivity values when tested with several samples of prostate image. The results obtained compares favourably well with results of previous works. The result obtained in this work can facilitate expert's function of identifying suspected cancerous regions within the prostate that will be subjected to biopsy investigation. Trans-rectal ultrasound guided prostate biopsy remains the reference standard for detection of prostate cancer [22] till date. Therefore this work will ensure a reduction of biopsies since sites of investigation are located with scientific accuracy.

The application of the result of this research will go a long way to ensuring early detection of cancer and consequently a reduction in death rates due to undetected cancer. The analysis of medical images using artificial intelligence techniques like segmentation therefore can accurately and successfully assist medical experts in diagnosing disease especially cancer of the prostate. It is believed that the results obtained in this work will go a long way to assisting medical professionals involved in managing prostate disease to provide both routine services and required reliable diagnosis.

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