Performance Measurement of Prostate Gland Segmentation Approaches in Transrectal Ultrasound and Magnetic Resonance Images

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Abstract

In the Twenty-first century cancer is a serve threat to human lives. As per cancer facts and figures of the American Cancer Society, 26% estimated new cases of prostate cancer in males will be diagnosed in 2021, whereas 11% will die because of this disease. To diagnose such disease segmentation plays a vital role in detection and treatment. To determine problems in the prostate, transrectal ultrasound and magnetic resonance images are employed. Finding the exact shape and size of the prostate gland is a big challenge in the field of medical image segmentation. This research presented various techniques through which one can segment the shape and size of the prostate gland for further diagnosis and treatment. The proposed work first developed the region-based segmentation method. Secondly used the level set function and optimized it by using a genetic algorithm, and at last, used the k-mean machine learning approach to optimize results. This paper evaluates the performance of segmentation algorithms on transrectal ultrasound and magnetic resonance images by using the performance matrix-like accuracy, sensitivity specificity, mean square error, and Dice similarity coefficient. The k- mean clustering machine learning approach has given the best-optimized performance with the extraction of accurate shape and size of the prostate with the accuracy of 96.3%.

Keywords

Prostate cancer, segmentation, level set, region growing, genetic algorithm, clustering.

1. Introduction

In the twenty-first century, cancer is a serve threat to human lives. As per cancer facts and figures of the American Cancer Society, 248,530 estimated new cases of prostate cancer in males will be diagnosed in 2021, whereas 34,130 will die because of the disease in the US [1]. As per records of prostate cancer incidences in India, the rate of prostate cancer has increased [2].

The prostate gland is a part of men's reproductive system. The prostate gland acts as a muscle and it generates seminal fluid to protect the sperms [3][4]. Prostate cancer is found in the prostate gland when an anomalous cell increases more rapidly than a normal prostate and may be converted into a malignant tumor. For finding the abnormality, initially, the doctor uses a prostate antigen test, digital rectal examination, and, biopsy. For detecting prostate cancer, there are some common symptoms like feeling uneasy in the pelvic area with pain, prostatitis, frequent urination, pain at the time of urination, blood in urine, men's infertility, and, hematospermia. Figure 1 shows the structure of the prostate gland located beneath of bladder [5].

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Prostate segmentation performs a vital role in various phases of medical treatment. The size, shape, and volume of the prostate can be directly determined by prostate segmentation. Such shape, size, and volume of the prostate help in the diagnosis of prostate diseases [4]. The finding of the perimeter, volume, and counter of the prostate is very helpful in the various treatments and monitoring of prostate diseases like BPH, prostatic brachytherapy [4]. Parallel to this, segmentation of the prostatic gland accelerated the procedure of tumor localization in a biopsy and radiotherapy. Even so, manual prostate segmentation is not a simple job, which is always sensitive to internal and external observer dispersion. Recently, automatic computerized techniques are being explored to carry out the segmentation prostate and its performance evaluation.

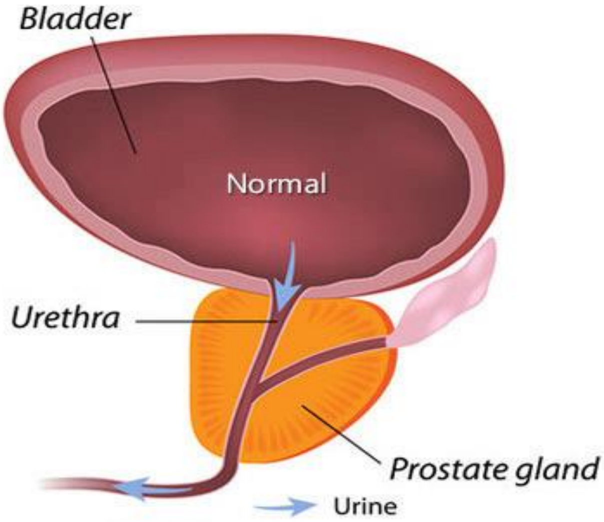


Figure 1: Prostate gland below the bladder

2. Transrectal Ultrasound and Imaging Method

The transrectal imaging method is also recognized as prostate ultrasound or endorectal sonography. The key role of the endorectal sonography method is to bring out men's prostate gland to detect and diagnose symptoms such as prostatitis, prostate cancer [6], pelvic pain, urinary tract infections, hematospermia, and problems related to men's infertility [3]. Because of its low cost, handy, systematic procedure transrectal ultrasonography is the most popular image modality.

The transrectal ultrasound imaging modality employed the concept of the ultrasound system. Ultrasound images of the prostate were captured with the help of transducer probes covered with a safely replaceable cover with gel. Doctors used to examine the prostate-specific antigen level to forecast the symptoms brought out due to deformities in the prostate gland if the PSA level is high [3].

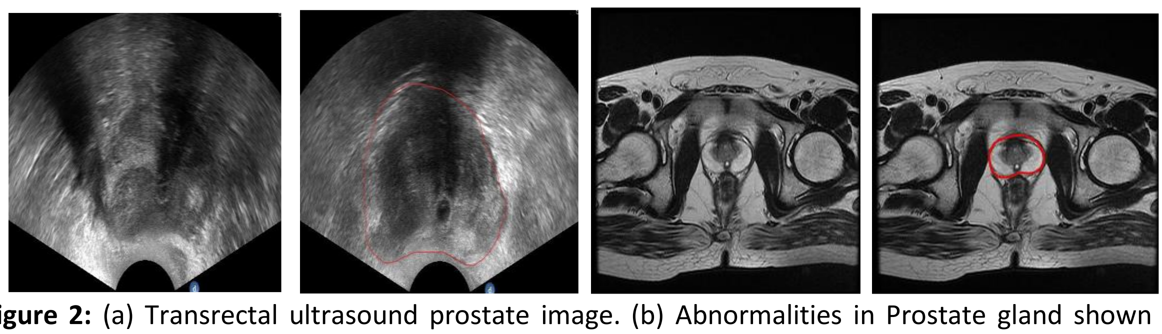


Figure 2: (a) Transrectal ultrasound prostate image. (b) Abnormalities in Prostate gland shown in Trans-rectal image marked by an expert. (c) Normal magnetic resonance prostate image. (d) Delineated prostate magnetic resonance image.

3. Magnetic Resonance Imaging

The magnetic resonance imaging techniques employ radio frequency pulses, magnetic fields, and computers to construct a completed image of the human body. Radiologists and oncologists utilize prostate MRI to evaluate the area of prostate cancer and detect whether it has spread or not. For the diagnosis of conditions, you have like infection and enlargement of the prostate, doctors may employ such images [9]. The use of standard T2 weighted MRI in the diagnosis, staging, and treatment of prostate cancer is maturing and extends from center to center. Normally, MR images have poor specificity and slightly good sensitivity [10].

4. Theoretical Consideration

The purpose of processing image segmentation and extraction of a particular prostate region is referred to as a region of interest. This can help the radiologist to identify the regions which require examination. In prostate TRUS and MR imaging, the objective of extracting a region of interest is to find the region present in the prostate which is likely to have prostate cancer. The region obtained should contain the region marked by experts [8]. Prostate image segmentation can be accomplished with the help of a counter segmentation process, region-based segmentation, machine learning-based supervised, and unsupervised image segmentation [7][4].

5. Seeded Region Growing Technique

It is a basic image segmentation technique. The seeding is used to start the process of segmentation. The seeding point may be automatic or manual. The main working principle of seed region growing is that the process starts using a single image's pixel and it continuously grows a region [11].

Region growing based image segmentation is used to extract the region from transrectal ultrasound prostate and MR prostate images. The region is the segmented area extracted from an image. This process includes all nearby pixels of images that show homogeneity with starting a single image's pixel [11]. Vinicius R, P. Borges, Maria Cristina F. de Oliveira proposed region growing based image segmentation for 2D microscopy digital images [12].

Erwin, Saparudin, in this paper proposed performance analysis of seed point-based region growing method [13]. The comparison is with image thresholding. Segmentation is done for the Berkeley segmentation database (BSDS). The author concluded that the region growing segmentation procedure results in clearer and more accurate boundary detection than the thresholding technique implemented for the same objective.

The region growing consists of the splitting and merging process. This process divides an image into uniform regions The splitting process divides an input image into several small regions generated using manual seeding. The process of spitting continues until no further split occurs. The reverse process of image split to generate an extracted region homogeneity defines uniformity in the splitting process [11][13].

The Euclidean distance between the two similar pixels is given by

$$\sigma(P,c) = \frac{min(\sum q\varepsilon W(P) d(qc_i))}{|W(P)|} \tag{1}$$

When the standard deviation of intensity is less than a threshold value, a statistically homogeneous region is defined for intensity level images. The standard deviation is given as

$$\sigma = \left[\frac{1}{n-1}\int_{j=1}^{n}(x_i - x)^2\right] \tag{2}$$

6. Related Work: Level Set Technique

In this technique, an interesting contour is a zero-level set of a level set equation. This status is fulfilled by the signed distance equation $|d\psi|=1$. The entire domain of an energy function gives a signed distance property. When the function is set as $|d\psi|=0$. Then the function is found far from the zero-level set [15]. The motion equation of the LS is

$$\frac{d\psi}{dt} = \nu.\nabla\Psi = 0 \tag{3}$$

Here a = (u, v, w), shows the fitness function, and u, v, and w are velocity or fitness fields concerning i, j, and k coordinates. The LS modified equation is

$$\frac{\psi(x+1)-\psi(x)}{\Delta t} + \vec{v}(x).\nu\nabla\psi \tag{4}$$

According to a special derivative, the equation becomes

$$\frac{\psi(x+1)-\psi(x)}{\Delta t} + u(x)\psi_i(x) + v(x)\psi_j(x) + w(x)\psi_k(x) = 0 \tag{5}$$

The level-set technique is employed to a substantial extent in the area of medical image analysis. As compared to segmented prostates by manual methods, a technique like optimization provides good results concerning shape training images and mean shape images [16].

7. Genetic Algorithm

A genetic algorithm is applied in two steps. The first step involves image training which obtains different textures, shapes, and regions. The training data performance of training data is obtained in the second stage where a genetic algorithm produces contour selection, crossover, and mutation. This is the stage that produces the next generation. To generate a new generation, the section of an individual is an important step. According to the fitness function, the individual gets selected [4][15][16].

$$A[\,Selecting\ the\ ith\ individual\,] = b'(1-b)(r-1) \tag{6}$$

Where: b = probability of best individual selection, A = population size, r = individual rank

$$b' = \frac{b}{1-(1-b)^p} \tag{7}$$

Where p = probability of an individual

Stopping criteria are achieved until the genetic algorithm generates a new generation According to the study, the most accepted stopping criteria are maximum population generation. [4][17].

8. Unsupervised Cluster-based Image Segmentation

The cluster-based segmentation method is the same as the classification method except that the clustering technique is an unsupervised technique. To perform the segmentation of the TRUS image, the cluster-based technique utilizes the iteration mechanism between the properties of each class. The process of TRUS image segmentation can be carried out using a well-known k-means unsupervised algorithm [18][19][20][21][22]. A cluster-based algorithm is used for the classification of a class of data set with predefined clusters. It is basically to cluster N data points with M-dimensional feature space into clusters. The classification space F can be defined as

$$F_a = [f_{a1}, f_{a2}, \dots\dots.. f_{aN}]^T , where\ a = 1,2,3 \dots.. M \tag{8}$$

The goal of this technique is to calculate the lower value of the addition of the square distance within the cluster between the pixel and the cluster center by moving pixels from one cluster to another cluster. The objective function for a cluster is given as

$$\in = \sum_{b=1}^{x} D^2\ (b, c) \tag{9}$$

where D (j, k) is the Euclidean distance of the pixel from the mean of the cluster. The cluster is defined as

$$D^2(b, c) = \sum_{a=1}^{M} [f_{a1} - U(b, a)^2] * W(b, a) \tag{10}$$

Here, u (b, c) = features mean with the cluster and W (b, a) = weighing factor [8].

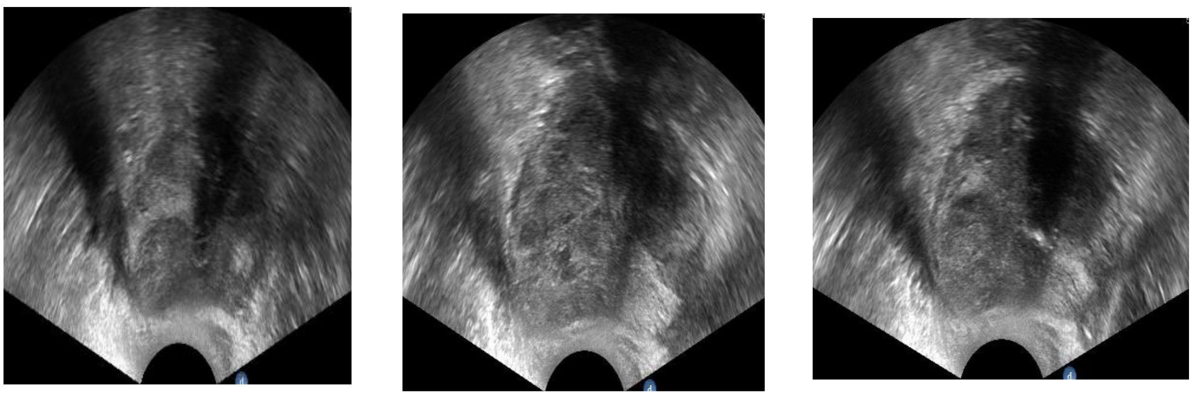
9. Experimental consideration/materials and methods

This research has been conducted with images captured with the approval of the Institutional Ethics Committee and with the taking permission of patients. The proposed experiments have been performed on a Windows machine with a configuration of Intel i5 CPU (3.4 GHz). The graphical user interface has been developed in MATLAB

T2W axial magnetic resonance images were generated using a human body. 1.5T GE Medical Systems (SIGNA HDxt) at an image size of 512 x 512. The 2-D TRUS images were acquired using Philips Medical Systems with a CURVED LINEAR transducer probe. The 2-D TRUS image size is 600 x 800. The TRUS and MR image databases contained 400 images each.

10. TRUS and MR images prostate database with ground truth

The required ground truths were generated by experienced radiologists and oncologists to check the performance of prostate segmentation algorithms.



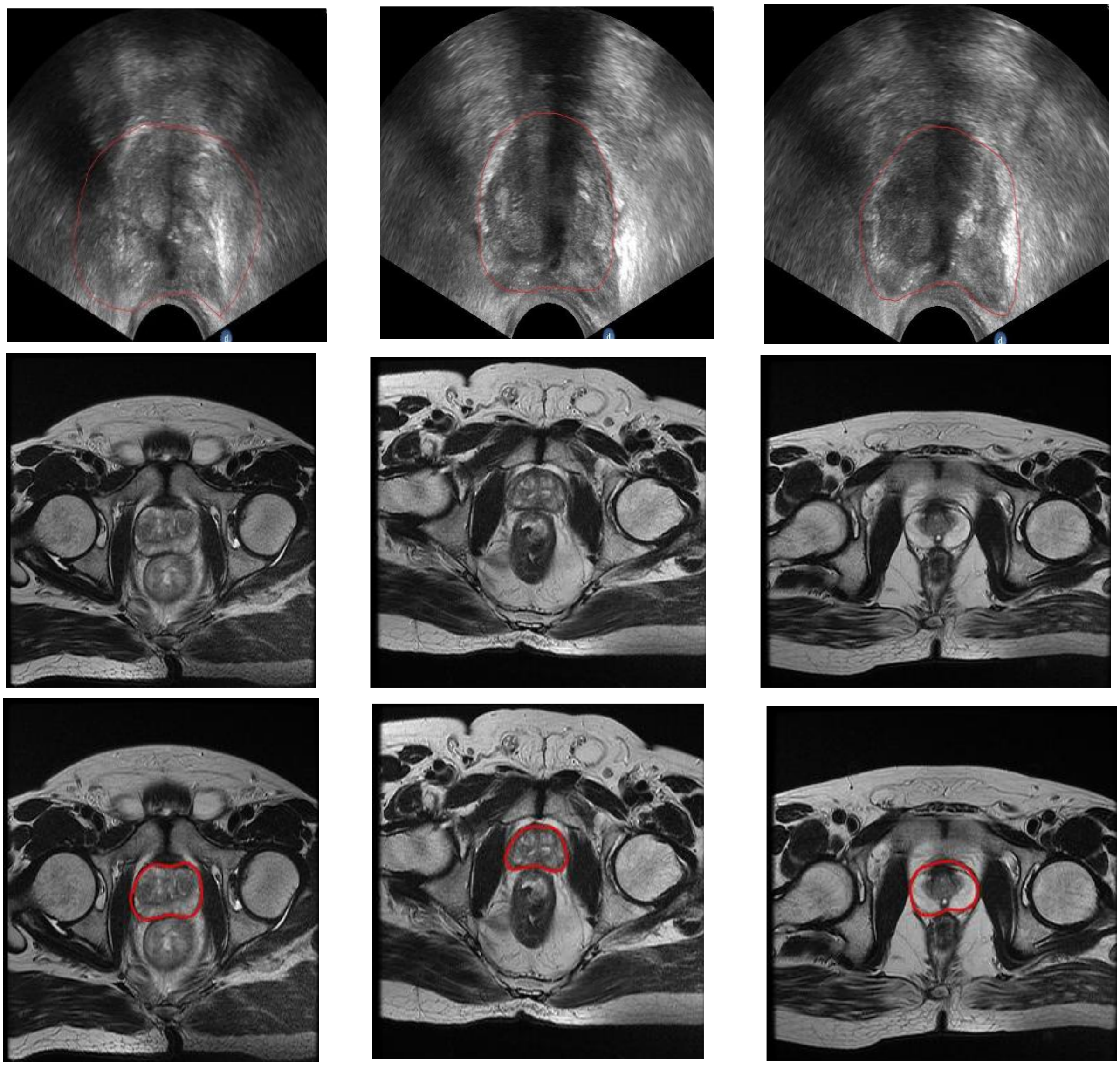


Figure 3: TRUS and MR prostate images database with and without ground truth

The implementation of prostate gland extraction consists of four separate techniques. The process of region extraction and detection is performed by a region growing level set, level set genetic algorithm, and k-means clustering. These techniques are used for the segmentation of TRUS prostate and MR prostate images.

11. Seed guided region growing process

The seeding region growing has a region split and region merge process. The split rapidly divides an input image into small homogeneous regions.

Split Phase: - A spilled phase provides the generation of a quadtree structure where nodes at each level result in the split of images into homogeneous sub-images with regular interval sizes. The set of small regions in the equal and regular structure created by the split process will be the set of input regions for the merge phase.

Merge Phase: - In the region merge process, nearby small regions are generated by image split. The iteration process helps to merge the small regions generated by the split to build a large image. The process of merging will continue until no more merges are possible.

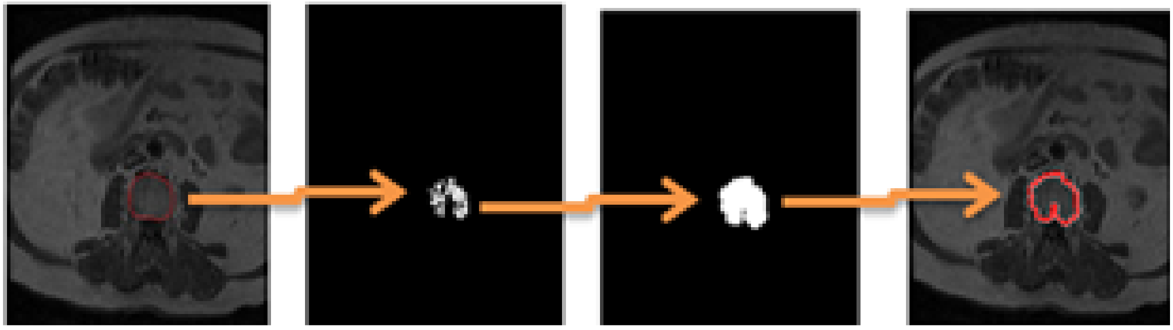


Figure 4: Experimentation output for Sees guided region growing process

12. Level Set Genetic Algorithm

LSM was used for segmenting prostatic images. Segmented filtered images were utilized as input images. The classification of the objects is achieved by feature extraction. To deal with the contours of the prostate, the features are extracted from the training set. A genetic algorithm is applied to optimize which decreases the need for an energy equation by the fitness function. It is a value of the individual population. A new generation is obtained using this value. After performing numerous operations, a contour is detected on the prostate gland. We exercise the following steps to obtain desired level-set genetic algorithm.

"Training Images: Manually Segmented image

- Extract the feature
- Mean Shape
- Shape variability
- Texture
- Mean position

Describe shape with help of the LSM

$$\psi[w,p](x,y) = \vec{\psi}\,(\overline{x},\overline{y}) + \sum_{j=1}^{k} w_j \psi_j\,((\overline{x},\overline{y}). \quad (11)$$

Set a threshold of fitness or number of generations > 100

for

Is fitness > number of generations > 100

→ Describe 'n' individuals of the genetic population as pose and weight parameters of the above equation. The curve is segmented by each individual.

→ Derive fitness score (0-1000) on test images

→Fitness score == 0: contour found outside the prostate.

else

→ Fitness score == 1000: the prostate encircles by segmenting counter

→ Execute genetic selection, crossover, and mutation to generate a new generation of segmenting contours

→ Number of generations = number of generations + 1

End.

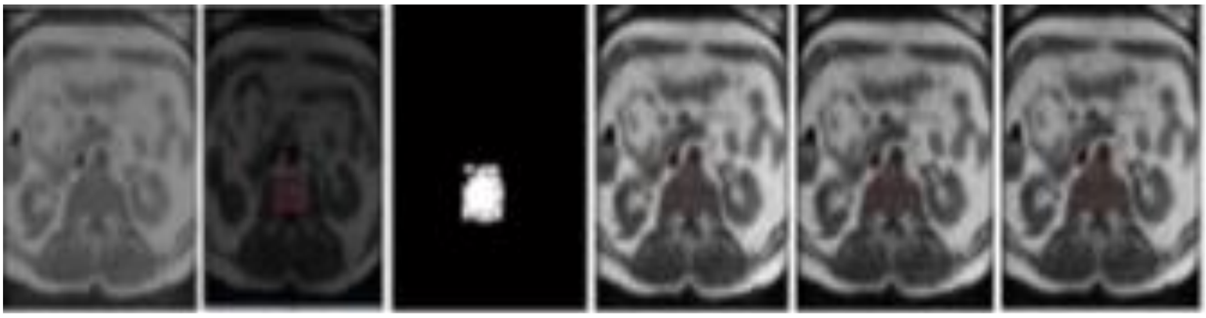


Figure 5: Experimentation output for level set and level Set genetic algorithm

13. Unsupervised k-means clustering process

To segment and extract the prostate area from the TRUS image, a multi-stage segmentation algorithm is proposed. This consists of five different stages.

1. Build knowledge-based rules before performing extraction and segmentation of the prostate. Some rules are applied to the proposed technique.
    a. TRUS image consists of different regions namely: The prostate, background, and tissues around the prostate.
    b. Background of the image should be black.
    c. Prostate Gray level should be low in comparison to tissues around the prostate.
    d. The prostate has a smooth curvature shape.
2. Perform image enhancement to achieve better segmentation output. Noise has to be minimized and images for further processing should be enhanced.
3. Select the cluster by defining its centroid. The k-means cluster process works on the computation of Euclidean distances between the data sets of distinct classes created by defining clusters and each cluster must have a centroid value.
4. Detection of prostate boundaries. The process of extraction of the prostate has a clustering technique is used in the process of extraction of the prostate. Initially, centroid and cluster are initiated. Calculate the Euclidean distance between the data sets of each class.
5. Extraction of the prostate image after computation of the Pythagorean distance between points from data sets. The algorithm works along boundaries where two distinct classes are produced. The final stage has two classes where one class represents the prostate and the other class represents the background.

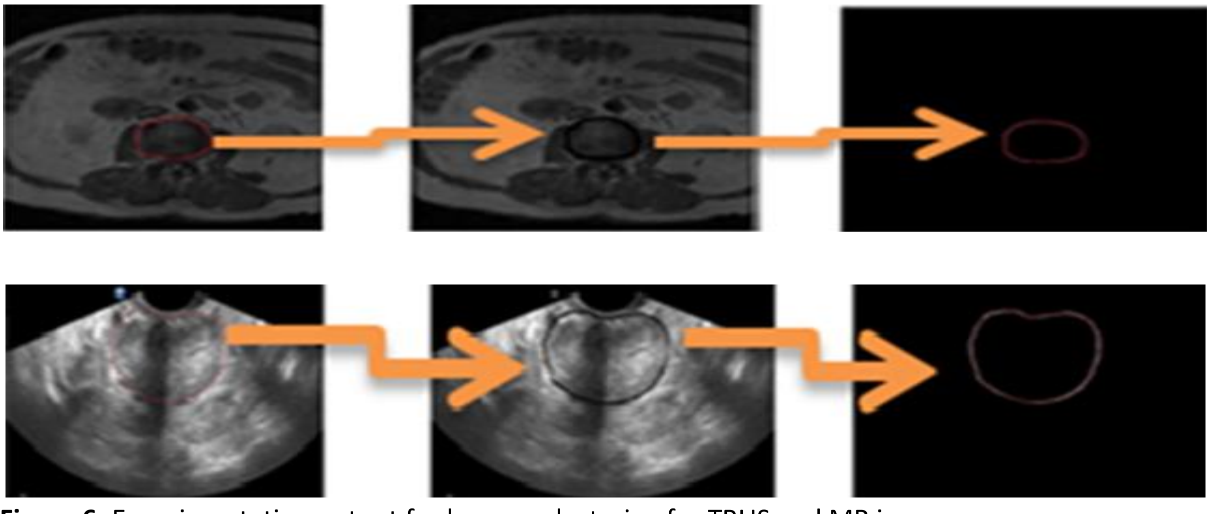


Figure 6: Experimentation output for k-mean clustering for TRUS and MR images

14. The Result, Analysis and Discussion

To find the performance of the experiment, ground truth images were developed as per the MICCAI prostate the challenges. Manual segmentations are performed by competent radiotherapists and confirmed by a professional urologist consultant. In the field of radiology and urology, these professionals have 12 years of experience. The proposed methods were evaluated for the patient's TRUS and MR images collected from the hospital.

Table 1: Overall performance parameters evaluation of prostate TRUS images

Performance parameters	Segmentation algorithm			
	Region growing	Level set	Level set genetic algorithm	k-mean clustering
MSE (mm)	0.129	---	---	0.179
Accuracy	0.188	---	---	0.737
Sensitivity	0.046	---	---	0.977
Specificity	0.989	---	---	0.268
DSC (mm)	0.083	---	---	0.983

Table 2: Overall performance parameters evaluation of prostate MR images

Performance parameters	Segmentation algorithm			
	Region growing	Level set	Level set genetic algorithm	k-mean clustering
MSE (mm)	0.059	1.46±0.3	1.48±0.3	0.200
Accuracy	0.045	0.429	0.705	0.963
Sensitivity	0.210	0.325	0.390	0.977
Specificity	0.970	0.956	0.913	0.195
DSC (mm)	0.956	0.485	0.496	0.984

The four proposed methods region growing, level set, level set genetic algorithm and clustering methods have been compared and evaluated performance parameters for the patient's TRUS prostate and MR prostate images that were collected from Bharti Vidyapeeth Hospital Pune India. The study protocol was reviewed. A quantitative study has been done for the proposed methods using performance parameters MSE, DSC, Specificity, Sensitivity, and Accuracy. Values of performance parameters for all prostate images are shown in Tables 1 and 2.

The first level set method is used on test images. After the experimentation, only 42.9163% accuracy was achieved along with, MSE 1.4696±0.3mm, and DSC 0.4853mm. Finally, it is observed that when a genetic algorithm is applied to the level set function, then achieved optimized results in terms of performance parameters as shown in table 2. Accuracy increased to 70.5180%. In the end, the LSM and a genetic algorithm are integrated and compared, showing optimized results.

Here we employed an unsupervised machine learning approach to get a more accurate result. After the experimentation, the k means clustering method segmented and detected the prostate shape and size accurately. K means the clustering approach gives a good result on TRUS images. On the transrectal ultrasound prostate images, it achieved approximately 73.7 % accuracy with MSE and DSE values of 0.179 mm, 0.983, respectively.

Finally, we achieved approximately 96% segmentation accuracy of prostate magnetic resonance images along with overall MSE and DSE values of 0.200mm, 0.984mm respectively, using k-mean clustering.

The scope of this research is limited to image processing and Machine learning Technique. Here we faced difficulties in implementing a level set genetic algorithm on TRUS images. In the next step in development, we can use deep learning approaches to improve performance.

15. Conclusion

Prostate cancer region extraction and segmentation using manual seeded region growing technique, level sets, level set genetic algorithm, and unsupervised cluster-based technique have been implemented. The performance parameters for each of these techniques presented and compared. The size of an extracted and segmented region from the TRUS and MR prostate images depends upon the starting seeding points. The region grows along the seed point, computing nearby similar pixel data elements present in an image. In this experiment, it has been observed that regardless of image similarities and noise, techniques were used here to segment the prostate gland surrounding tissues properly. Here we tried a genetic algorithm on a level-set function, that involves complex features because of that applying segmentation of prostate MR images becomes tiresome. In the level set, the energy fitness function is used, but optimization procedures like genetic algorithms keep away from its uses. In the comparison of level set and level set genetic algorithm segmentation techniques, the level-set genetic algorithm technique provides better and optimized results. The cluster technique generates the new small clusters and their centroids and produces small regions of similar image pixel data sets. It is concluded that the region extraction and segmentation using the automatic unsupervised k-means cluster technique is efficient and more accurate than the manual seed point region growing, level set, and levels set genetic algorithm method.

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