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# A Hybrid Approach for Prostate Boundary detection using Ant Colony Optimization and Artificial Neural Network

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*Abstract:* **Number of Computer Vision and Machine Vision researchers concentrating on the field of Medical Diagnosis. Where some fruitful results came and help the experts or doctors to make the diagnosis process efficient and easy [20]. Prostate Cancer has a considerable impact on the life of adult men. So it is very important to detect Prostate Cancer at early stages. But the main barriers in this field are Poor image quality, presence of noise etc. restrict us to make exact decisions [8]. So the poor image quality, speckle noise & shadowing effects in ultrasound images i.e. the most common imaging technology used in most of the urologic clinics for the treatment of cancer, achieving an accurate, robust & fast performance in automatic boundary detection is difficult & time-consuming [3]. Moreover, manual contouring too is time-consuming & subject to inter-and intra-observer bias. A lot of work has been carried out in processing & segmentation of prostate boundary, but still there is a room for further improvement in this area. we proposed a new hybrid technique in which we pick two optimization techniques to deal with this issue. Ant Colony Optimization and Artificial Neural Network are use to get the prostate boundary also the results obtained after this experiment are also compared with the result given by the method where Genetic Algorithm optimization technique is used to get the prostate boundary.**

*Keywords:* **Computer Vision, Machine Vision, Prostate Cancer, Speckle Noise, Ant Colony Optimization, Artificial Neural Network.**

## I. INTRODUCTION

Prostate cancer is one of the most common types of cancer found in American men. It is estimated that there will be about 230,900 new cases of prostate cancer in the United States in 2004. It is no doubt that early detection of cancer will improve the survival rate tremendously [26, 27]. Transrectal ultrasound (TRUS) scanning of the prostate is commonly utilized as the routine manner of prostate cancer detection and diagnosis [1]. Boundaries and volumes obtained from TRUS images play a key role in clinical decisions, since accurate boundary delineation is essential to guarantee preservation of organ function while controlling organ-confined cancer [2]. It is very important to detect prostate cancer at early stages. Digital Rectal Examination (DRE), Prostate-Specific Antigen (PSA) test and Tran rectal Ultrasound (TRUS) are three most commonly used techniques in screening and diagnosing prostate cancer. A brief description of these techniques is provided in the following:

- **Digital Rectal Examination (DRE):** A digital rectal examination (DRE) is performed by a doctor during a regular office visit. In this examination, the doctor inserts a gloved finger into the rectum and feels the prostate gland through the rectal wall to check for abnormality. Rectal examination is inexpensive and relatively non-invasive. Also, it can be taught to non-professional health workers. However, its effectiveness depends on the skill and experience of the examiner. The effectiveness of DRE in diagnosing prostate cancer is questionable [4].

- **Prostate-Specific Antigen (PSA) Tests:**The PSA test has revolutionized the detection of prostate cancer since its introduction in the mid-1980s. A normal, healthy, 50-year-old male is generally believed to have a PSA value of less than 4.0 ng/ ml. Over the years, physicians have developed schemes that incorporate the readings of this test with other information for a more accurate diagnosis of the prostate cancer [4,5].

- **Trans rectal Ultrasound (TRUS) and Other Imaging Tests:**Prostatic imaging is possible by ultrasound or magnetic resonance imaging, which will be introduced in the next two sections [7]. Out of all the imaging techniques, ultrasound is most commonly used. There are two common uses of ultrasound imaging: The first is to guide the doctor in the biopsy procedure. The second use is in the establishment of the prostate's volume.

All the research on automatic prostate boundary detection for 2D ultrasound images can be classified into 3 main categories: Edge Based Methods, Texture Based Methods & Model Based Methods [18].

***Edge Based Methods***: The basic fundamental behind all the methods using this technique is to locate all the edges in the image. Then after edge selection & linking is performed on that located edges to outline the prostate boundary. The main advantage of this technique is that when the boundary is clearly defined, this method is quiet easy & straightforward. The shortcoming of this technique is it is difficult to distinguish false edges from real edges & to fill up missing boundary sections with anatomic knowledge, thereby comprising the robustness [7,9].

***Texture Based Methods:*** Another technique for prostate boundary detection is based upon texture discrimination. These methods does not find edges in an image, rather on the basis of measure of texture it characterizes the images into regions. Further, they produce an edge map of an image by creating a border between regions determined to have different textures [18].

***Model Based Detection Methods***: Most recent research has shown that model based segmentation methods are more efficient & powerful in locating object boundaries [18]. Also, some prior knowledge such as anatomic information, physical characteristics of objects & radiological features of imaging is integrated. Prostate ultrasound, also called Trans rectal ultrasound, provides images of a man's prostate gland and surrounding tissue. The exam typically requires insertion of an ultrasound probe into the rectum of the patient [11]. The probe sends and receives sound waves through the wall of the rectum into the prostate gland which is situated right in front of the rectum. In case of ACO Ants deposit a certain amount of pheromone while walking, & each ant probabilistically prefers to follow a direction rich in pheromone rather than a poorer one. Ants choosing the shorter path will more rapidly reconstitute the interrupted pheromone trail compared with those choosing the longer paths. Thus, the shorter path will receive a greater amount of pheromone per unit time, and in turn, a larger number of ants will choose the shorter path. Due to this positive feedback, all the ants will rapidly choose the shorter path. Ants prefer higher pheromone trail levels causing this accumulation to build up still faster on the shorter path [12,13]. So this way is used to find the boundary of prostate as boundary pixels of prostate possess similar properties and in this context we call each and every pixel which lies on the boundary of prostate is treated as ant in ACO and Ants can move in the proposed algorithm, according to the weights assigned to the Neural Network. In actual the weights assigned to the nodes of NN are actually pixel values associated with the pixels present at boundary of prostate. Where Ant colony optimization (ACO) is a heuristic method that imitates the behavior of real ants to solve discrete optimization problems. The created artificial ants behave like intelligent agents with memory and ability to see. These ants share their experiences in order to search optimal paths iteration by iteration. Ant colony optimization (ACO) is a multi-agent system that iteratively searches for optimal solutions [17]. Elements of optimal solutions are extracted according to the shortest path of ant tours. Ants deposit their searching reward, pheromone, on their passed paths. These feedbacks may attract other ants to follow partially with a probability called state transition rules. State transition rules imply that shorter and more ant-experienced paths attract more ants to pass through. As with real ants, not all ants follow the most attractive paths, instead a few ants try to explore new paths. The process of taking the maximal probability path is called exploitation, and the process of selecting the next path by probability is called exploration [21]. The characteristics of ACO algorithms are their explicit use of elements of previous solutions. The main underlying idea, loosely inspired by the behavior of real ants, is that of a parallel search over several constructive computational threads based on local problem data & on a dynamic memory structure containing information on the quality of previously obtained result. This collective behavior, emerging from the interaction of the different search threads has proved effective in solving combinatorial optimization (CO) problems. Set of computational concurrent asynchronous ants (a colony of agents) moves through states of the problem corresponding to partial solutions of the problem to solve [23]. By moving, each ant incrementally constructs a solution to the problem. When an ant completes a solution; or during the construction phase, the ant evaluates the solution & modifies the trail value on the components used in its solution. This Pheromone information will direct the search of the future ants. Two underlying mechanisms play an important role in the performance of Ant Colony Optimization: *Trail Evaporation* which in order to avoid unlimited accumulation of trails over same component decreases all trail values over time and *Daemon Actions* which can be used to implement centralized actions which cannot be performed by single ants, such as the invocation of a local optimization procedure, or the update of global information to be used to decide whether to bias the search process from a non-local perspective. Ants deposit a certain amount of pheromone while walking, & each ant probabilistically prefers to follow a direction rich in pheromone rather than a poorer one. Ants choosing the shorter path will more rapidly reconstitute the interrupted pheromone trail compared with those choosing the longer paths. Thus, the shorter path will receive a greater amount of pheromone per unit time, and in turn, a larger number of ants will choose the shorter path. Due to this positive feedback, all the ants will rapidly choose the shorter path. Ants prefer higher pheromone trail levels causing this accumulation to build up still faster on the shorter path.

## II. PROPOSED WORK

As this paper is the extension of our previous paper in which we proposed this method to detect the prostate boundary form Ultrasound images. This detection process requires ultrasound images as input image to the system after that to deal with the issue of speckle noise in case of US images we have proposed Snakes filter. After the removal of speckle noise, the next step is to take the expert observations. We here proposed to take the observations of 5 different experts who tell us about the idea of 12 different points, which according to then will lies on the boundary of the prostate and help to draw the boundary. So the basic idea is to get the initial estimate for the system to get the X and Y coordinates of points mentioned by the experts.

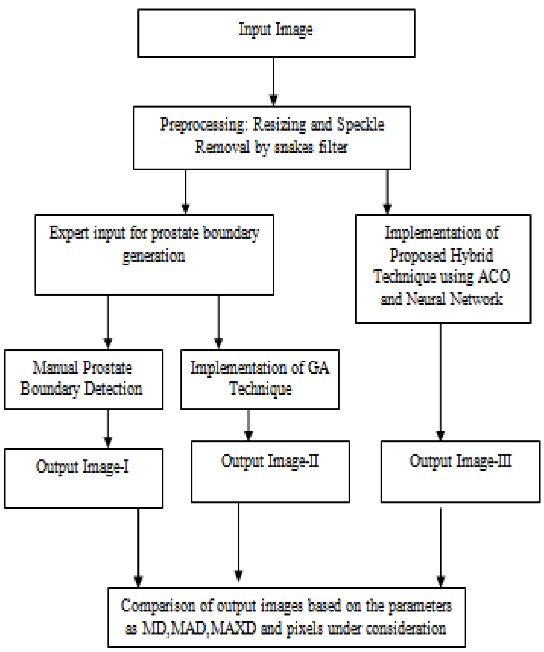


Fig: Proposed Methodology

After getting these coordinates input then we apply the concept of Genetic Algorithms to find the prostate boundary. Genetic Algorithm strategy considers these different observations as different populations. This algorithm firstly tries to reach to the center of prostate then with the reference of the centre draw the boundary of the prostate and get an output image. Then on the same image which earlier was the output of preprocessing step we apply the concept of Ant Colony Optimization and Artificial Neural Network. With the concepts of Ants, we consider Ants as those pixels which are the part of prostate boundary. And the different trail values of different pixels serve as the weights of Neural Network, which will helps to make the selection decision about the prostate boundary pixel. At the end the prostate boundary detected from GA and proposed hybrid method can be compared against the parameters as MD, MAXD and number of pixels under consideration and CPU speed.

***Algorithm of proposed Hybrid technique:***

1. Find Prostate boundary pixels to generate the weights of Neural Network **NN[][]** by checking the darkness and brightness in the neighborhood pixels.

2. **[Initialization]**
   Initialize $T_{iu}$ (Trail Level), $N_{iu}$ (Attractiveness) & other parameters of ACO with the help of array **NN[][].**

3. **[Construction]**
   For each ant K (currently in state i) do
   Repeat
   Choose in probability the state to move into
   Append the chosen move to the $K^{th}$ Ant's Set $Tabu_k$
   Until ant k has completed its solution
   End For

4. **[Trail Update]**
   For each ant move (i-u) do
   Compute sum ($T_{iu}$)
   Update the Trail Matrix
   End For

5. **[Terminating Condition]**
   If not (end test) go to step3

## III. RESULTS AND DISCUSSIONS

The performance of the current algorithm based on ACO is evaluated by computing The Mean Difference (MD) computed as

$$MD = 1/N \left( \sum_{j=1}^{n} Dj \right)$$

The Maximum Difference (MAXD) computed as

$$MAXD = \max ( |Dj| )$$

Number of Pixels considered for Boundary Construction, CPU Time, Number of Iterations needed. The Mean Difference (MD) is a measure of segmentation bias & is used as a local measure of algorithm's performance. Dj denotes the difference of a point j from the centroid of the segmented surface. The

Maximum Difference (MAXD) is a measure of maximum error and is computed as maximum of Dj. The next three parameters i.e. Number of pixels considered, Iterations needed, CPU time measures the algorithm efficiency & global optimization of the algorithm. Based on these parameters we propose the following results:

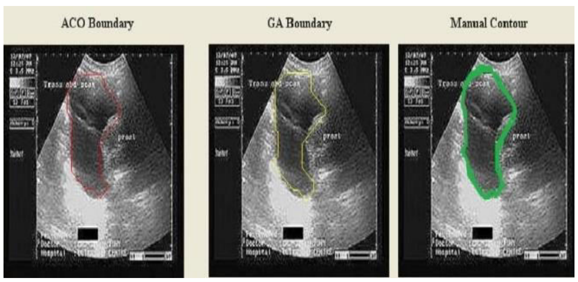


Figure 2: Test Results of Image-1

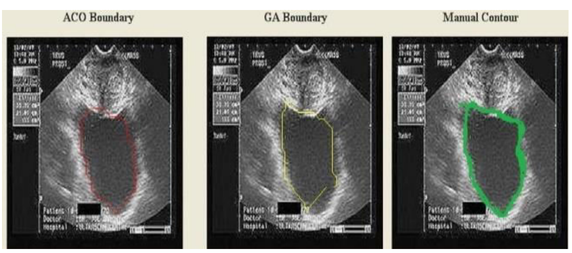


Figure 3: Test Results of Image-2

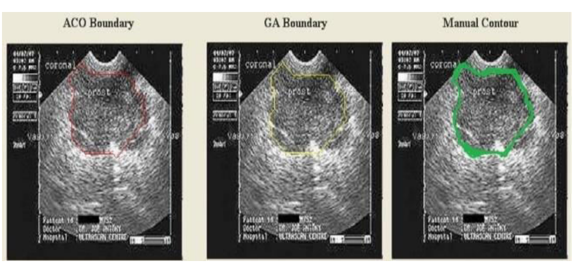


Figure 4: Test Results of Image-3

**Table 1**: Different parameters used to find results

| Image | Algorithm | MD | MAXD | Pixels Considered | CPU Time | No. of Iterations |
|---|---|---|---|---|---|---|
| Image-1 | GA | -0.669 | 6.5314 | 10575 | 4.5 | 65688 |
| | Proposed | 0.1821 | 2.4078 | 9928 | 1.0 | 65536 |
| | | | | | | |
| Image-2 | GA | 0.2340 | 1.1721 | 12656 | 3.5 | 65668 |
| | Proposed | 0.1290 | 1.1191 | 12654 | 1.5 | 65536 |
| | | | | | | |
| Image-3 | GA | 1.0229 | 7.8739 | 10270 | 4.6 | 65568 |
| | Proposed | 3.4688 | 8.6328 | 10160 | 1.7 | 65536 |

## IV. CONCLUSION

Prostate Cancer has a considerable impact on the quality of life of adult men and it is difficult to detect the Prostate Cancer at early stages [7]. Also the Poor image quality of ultrasound images causes difficulty in disease diagnosis. Further Manual Contouring is time-consuming & subject to inter-and intra-observer bias. The Inefficiency of Traditional Edge Detectors in Prostate Boundary detection so there is a need to automate boundary detection process to decrease clinician's workload & reduce segmentation time [9]. So to deal with all these issues we proposed a hybrid approach in this field. This contains Artificial Neural Network and Ant Colony Optimization. The ability of ACO to work with large solution domain and The ability of ANN to make decisions on the basis of weights assigned to different nodes will help to work good under this problem area where we have to perform under the large number of pixels contained by the ultrasound image. Also preprocessing step improves the detection process by improving the visibility of the input image. The different statistical parameters used like MD, MAXD, number of iterations etc. in result section showed that accurate and efficient working of proposed algorithm.

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