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# Prostate Boundary Detection from Ultrasound Images using Ant Colony Optimization

**Vikas Wasson[1], Baljit Singh[2]**

*[1]Faculty CSE, IET BHADDAL*
*Email: vikaswasson21@yahoo.co.in*

*[2]Faculty CSE, BBSBEC Fatehgarh Sahib*
*Email: baljitkhehra@rediffmail.com*

**Astract**

Prostate Cancer & diseases is quite common in elderly men. Early detection of prostate cancer is very essential for the success of treatment. In the diagnosis & treatment of prostate diseases, prostate boundary detection from sonography images plays a key role. However, because of the poor image quality of ultra sonograms, prostate boundary detection is still difficult & challenging task & no efficient & consistent solution has yet been found. For improving the efficiency, they need is to automate the boundary detection process for which number of methods has been proposed. In this paper, a new method based on Ant Colony Optimization is proposed, which will increase efficiency & minimize user involvement in prostate boundary detection from ultrasound images.

**Keywords:** Prostate, boundary detection, Ant Colony Optimization, cancer, sonograms

## I. Introduction

### *A. Prostate Diseases*

Prostate diseases are quite common in elderly men. Prostate cancer is one of the most common types of cancer found in American Men, indeed it is the second-leading cause of cancer death there. Prostate Cancer is usually curable if it is diagnosed early. Therefore, it is very important to detect prostate cancer at early stages. Ultrasound imaging is the most common imaging technology used in urologic clinics because it is a fast, portable &cost-effective medical imaging technology offering interactive visualization of the underlying anatomic structure in real time & has the ability to show dynamic structure within the body. For this reason, TRUS is commonly used for diagnosis of prostates, detection & staging of prostate cancer, and real time image guidance of therapeutic procedures [2, 3].However, achieving an accurate, robust & fast performance in automatic boundary identification still is a challenging task owing to the relatively poor image quality of ultra sonograms, speckle noise & shadowing [4]. For this reason, manual contouring is currently the only robust, reliable segmentation procedure available for the TRUS of the prostate. Unfortunately, this process is time-consuming & arduous because the results are very much dependent on the observer's experience & vary between several observers. The result also may vary for the cases when the observer is performing the same job at different times. To improve the efficiency, a possible solution is to automate the boundary detection process with minimal manual involvement especially for computer-assisted surgery [5]. Number of methods has been proposed to automatically detect prostate boundaries (partial or full) from ultrasound images applied both to 2D as well as 3D prostate boundary detection [1, 5-19].

### B. Ant colony optimization (ACO)

It 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. 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.

## II. Related Work

In 2003, Fan Shao & K.V. Ling presented a paper on *prostate boundary detection from ultrasound images*. They described a number of methods used for prostate boundary detection i.e. *Edge based & Model Based Methods*. Each method is defined with its relevant advantages & disadvantages. Further, they concluded that *Model Based Methods* will likely be the most immediately successful [1].

In 2003, Joseph Awad & Galil proposed a multi-stage algorithm for Prostate Boundary Detection.

Firstly, they describe that traditional Edge Detection Filters like *Sobel* and *Roberts* are not suitable for smoothening of US images and pre-processed the images using *Sticks Technique*.

Finally, this enhanced image is further segmented to detect the Prostate Boundary [7].

In 2004, Ahmed Jendoubi et al presented an improved modeling technique to the segmentation of prostate Ultrasound Images using deformable Snakes Model. Firstly, the Proposed Snakes Model is described. Finally, with results it was described that the proposed model produces efficient segmentation results [20].

In 2007, Guokuan Li et al proposed a new Surface re-construction model for detecting Prostate Boundary from Ultra-Sound images. Also, it was described that 2D deformable Snakes Model is effective only when the initial contour is close enough to the real contour in the ultrasound images [22].

**Image Pre-Processing**
- Filter Image using Sticks Filter

↓

**Training Process**
- Manually chose some points representing a prostate shape from different images
- Initial Contour: Mean of the Training Shapes

↓

**Boundary Searching using ACO**
- Use Initial Contour as a Starting Point
- Apply ACO to search further Boundary

Ruo yun wu & KV Ling in 2000 presented a model based boundary recognition system for TRUS images using Genetic Algorithm. Firstly the image is modeled and then to increase the robustness & speed of searching, genetic algorithm is used on this modeled image for prostate boundary searching. Further it was concluded that this GA based system only applicable for images having centered position of Prostate and employing Sticks Filter will further improve system's Performance [16].

In 2007, De-Sian et al proposed a improved technique for Edge Detection based on Ant Colony Optimization. Firstly, they described that traditional edge detection approaches always result in broken pieces, possibly the loss of some important edges. Further, ACO based segmentation technique is applied to compensate for these broken edges [23].

In 2009, Nohridda & Norila in their work investigated the effectiveness of Genetic Algorithms & Ant Colony Optimization for RPP problem. Finally, the results of both GA & ACO were compared and from results, it was described that ACO algorithm is much more efficient than GA in terms of time complexity & number of iterations needed [21].

## III. Methodology / Planning of Work

The following diagram shows the process by which proposed problem will be solved:

A. **[Pre-processing]**
   - Remove Speckle noise & make the boundary more specific using Sticks Filter

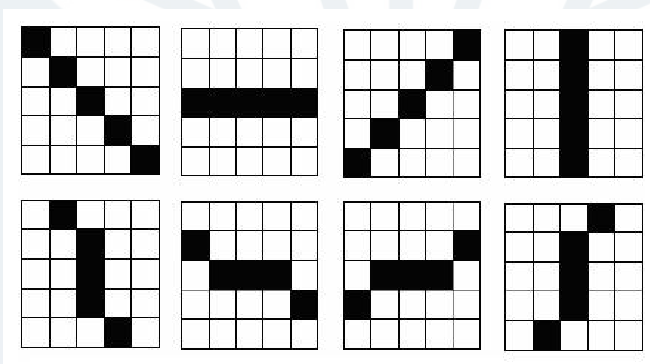
B. **[Training Process]**
   - Identify Shape Representation to determine Initial Contour

C. **[Apply ACO]**

- Initialize
- Repeat steps until convergence
- condition met
- Construction/ Solution Build-up
- (Searching Further Boundary
- Points)
- Evaluate Fitness/ Objective Function
- Trail Update (Local & Global)
- Terminating (Met Convergence Condition/ All Boundary Points identified)

### i) Image Pre-processing

- Image Pre-processing includes enhancing the image using Sticks Technique
- Pre-processing is necessary because the input Ultra-sound image usually contains Speckle Noise causing difficulty in finding Prostate points.
- So, to remove this speckle noise pre-processing is done using Sticks Technique.
- The stick filter determines the mean of neighbouring pixels in the direction of the stick - the most likely direction of the linear feature passing through ( x, y).
- Assuming n is the stick's length in pixels, there are 2*n-2 possible orientations of its can be arranged.

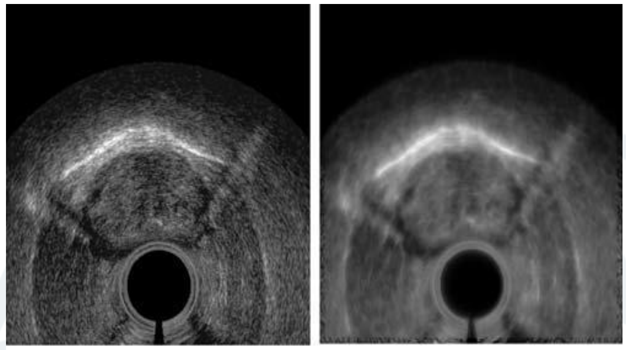


*A typical stick of length five pixels*

The sticks filter bank is applied to an image as follows.

- For each pixel in the image, each of the $2n - 2$ masks is superimposed on the image
- The mean intensity of pixels along each hypothesized line is computed.
- The mask that results in the largest mean intensity is taken as the most likely hypothesis.
- The resulting maximal average is assigned to the corresponding pixel in the output image.
- Let $s_1$, $s_2$, …, $s_2n-1$ be the stick filter masks. The output image, $g(x, y)$, is given by:

$$g(x,y) = \max_{i=1\ldots 2n-1} (f * s_i)(x,y)$$

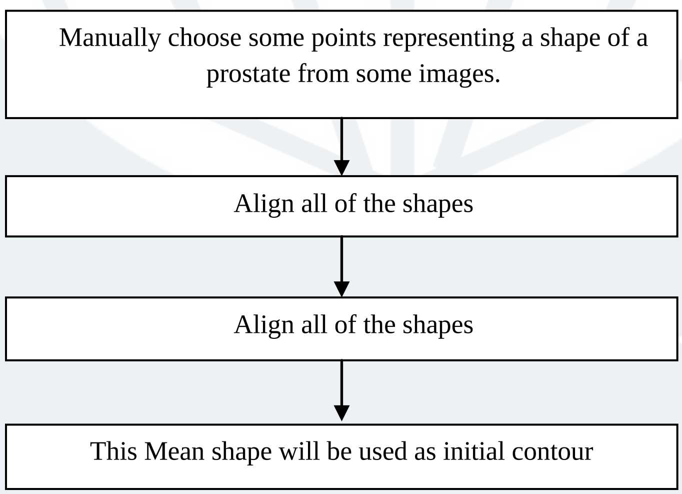


(a) (b)

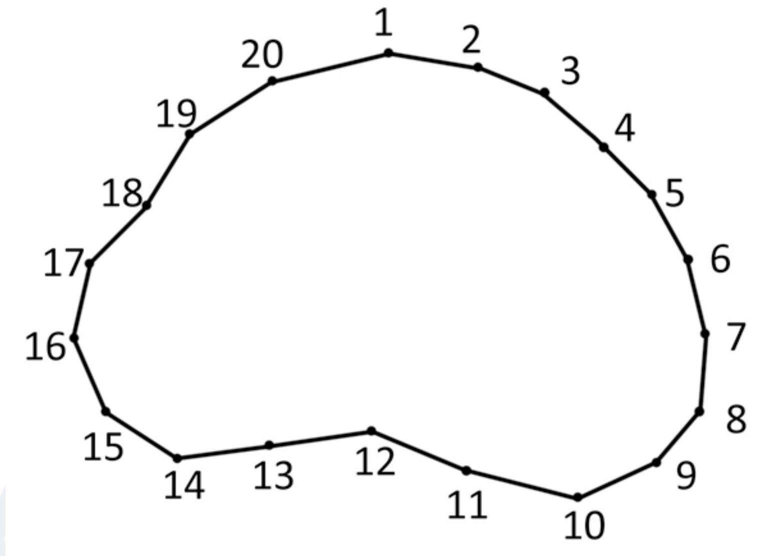
**a) US before Sticks b) After sticks**

### ii) **Training Process**

Training process is necessary in order to get a basis for shape representation. Illustration of the training process in this thesis is shown in figure.




**Point distribution model (PDM)** is performed to get the shape statistics. PDM is a model for representing the mean geometry of a shape from a training set of shapes .In PDM, a shape is represented by a set of points. Points are usually located in the boundary of the object. The labelling of the point is very important, because each particular part of the object is represented by the labelled point. An example of labelled points for the prostate is shown in figure:




*A set points representing a shape of prostate*

In this case, 20 points are chosen which represent a shape of prostate. Point number 1 is always located on the top canter of the prostate. Point number 12 is always located in the bottom centre of the prostate. The method works by modelling how different labelled points tend to move together as the shape varies. If the labelling is incorrect, with a particular point placed at different sites on each training shapes, the method will fail to capture shape variability.

### Aligning a set of shapes

X is a vector containing the x and y coordinate of the points in a shape with n number of points as follows

X=(x1, x2,……,y1, y2,…..)

Some vectors Xi, i = 1………..m, where m is the number of shapes, is then aligned using the following steps:

- Rotate, scale, and translate each shape to align with the first shape in the set.
- Repeat
  - Rotate Calculate the mean shape from the aligned shapes
  - Normalize the mean by aligning to the first shape
- Until the process converges

### Computing Mean Shape

Having a set of m aligned shapes; the mean shapes $\overline{X}$ now can be obtained using

$$\overline{X} = \frac{1}{m}\sum_{i=1}^{m} X_i$$

This mean shape is computed to be used as an initial contour for initialization.

**Construction:** The Searching begins with an initial boundary (consists of a list of boundary points) at an initial location in the image. Then each boundary point searches the area around itself (succeeding points), moves to the nearest strong points.
When an ant located at point i, the path visibility (attractiveness) between points i and j is defined as follows:

$$\eta_{ij} = \frac{V(p_j)}{\max\{\,1, |p_j - p_i|\}}$$

Where $P_i$ denotes the coordinates of point i and $P_j$ denotes the coordinates of point j as an adjacent point to i. The term V ($P_j$) represents the neighbouring difference of $P_j$ and is defined as follows:

V ($P_j$) = ( $\sum_{l \epsilon NE_i}$ | $P_j$- $P_i$ |) /no. of neighbours

- A large value for $\eta_{ij}$ exists.
- If V(Pi) = 0, then ant stops here (not a feasible point).

iii) **Boundary Searching using Ant Colony Optimization:**

a) **State Transition Rule:**

During the construction of a new solution the state transition rule is the phase where each ant decides which is the next state to move to. An ant goes to its next stop by the following path selection rule:

$$\text{STR} = \begin{cases} \underset{j \epsilon NE_i}{argmax} \left\{ [\tau_{ij}]^{\alpha} \cdot [\eta_{ij}]^{\beta} \right\}, & if\ q \le q_{0,} \\ J, & otherwise, \end{cases}$$

$$prob_{ij} = \begin{cases} \dfrac{[\tau_{ij}]^{\alpha} \cdot [\eta_{ij}]^{\beta}}{\sum_{j \epsilon NE_i} [\tau_{ij}]^{\alpha} \cdot [\eta_{ij}]^{\beta}} & , if\ j \epsilon NE_i , \end{cases}$$

Where is defined in Eq. $T_{ij}$denotes the pheromone trail between pixel i and j; α and β are two parameters determining the relative influence of the pheromone trail and the path visibility; q denotes a random variable, and J denotes a random variable selected according to the probability distribution given by Eq. It indicates that a parameter q0, satisfying 0 <= q0<= 1, determines the probability of an ant selecting *exploitation* or *exploration* as its next stop. In exploitation, as a probability of q0, the ant chooses the next stop by the largest relative influence.

Conversely, in exploration, the ant chooses the next stop according to the probability distribution of the relative influence with the probability of 1 - q0.

b) **Evaluate Fitness / Objective Function:**

The ACO often requires an objective function that assigns a fitness score to each solution in the current population. In our case, an ideal objective function should be able to give the highest score to the real boundary in every image. It can be observed that the prostate appears in an ultrasound image as a relatively dark region. The desired boundary position should be dark at the inner region and bright at the surrounding region. The objective function should be able to give a boundary high fitness score when the boundary is placed at the correct position i.e. the position where it is dark at inner region and bright at the surrounding region. When the succeeding boundary points don't match this fitness criterion, it is not considered as a feasible path. The procedure continues till it finds the optimal solution for prostate boundary detection.

**c) Trail Update:**

The pheromone trail of each edge will evaporate over time; it loses intensity if no more pheromone is laid down by other ants. For those edges that ants travelled in this iteration, their pheromone intensity can be updated by pheromone updating rule. Global & Local updating rules are generally used to update the pheromone trail.

**Amount of Pheromone Left= $(\text{distance})^{-1}$**
After pheromone evaporation occurs, the pheromone levels are updated with the extra pheromone laid by the ant(s) that just crossed the path in accordance with two rules:

**Local Update:** While constructing its tour, each ant modifies the pheromone by the Local Updating Rule i.e. $T_{ij}(t) = g^* Tij\ (t-1) + (i-g)\ T_0$

Where *g* is heuristically defined parameter (usually set to 0.9),
$T_0$ is Initial Pheromone Value & $T_0 = (n^*L_{nn})^{-}1$

Where $L_{nn}$ is the tour length produced by the execution of one ACO iteration without the pheromone component.

**Global Update:** After all the ants complete the path to goal, then the process of global updating is applied where ants will deposit its pheromone based on the path distance.

$T_{ij} = T_{ij}$ + (summation (1, k) $T_{ijk}$
Where $T_{ij}k = Q/L^k$ if ant k uses (I, j) in its tour
otherwise

Q is constant and is equal to number of nodes $L^k$is the length of path built by ants.
If we increase the number of ants in each iteration & repeat the algorithm, eventually we will get all the ants to move along a common path that happens to be the optimal solution.

- Parameters α and β determines the relative influence of the pheromone trail and the path visibility. Information in image content is always more important than in pheromone trail, thus, B > α is a general selection i.e. α = 1, β = 2.

- Parameter q0 determines the probability of the ant selecting the most important path. The value of q0 is always close to 1 and is usually set to q0 = 0.9.
- Two parameters T, g determines the initial value for the pheromone trails and the value is very close to 0. g is always small to let new pheromone trail mainly from previous pheromone trail i.e. $T_0$= 0.000001, g= 0.2.

## IV. Conclusions

As the prostate diseases & cancer in men increases day by day, there is a need for a fast & accurate automatic prostate boundary detection tool. In this paper, a new method based on Ant Colony Optimization is proposed which will increase efficiency & minimize user involvement in prostate boundary detection from ultrasound images.

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