GRAPH-BASED ACTIVE CONTOURS USING SHAPE PRIORS FOR PROSTATE SEGMENTATION WITH MRI

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ABSTRACT
Prostate segmentation based on magnetic resonance images is a challenging and important task in medical imaging with applications of guiding biopsy, surgery and therapy. While a fully automated method is highly desired for this application, it can be a very difficult task due to the structure and surrounding tissues of the prostate gland. Recently, graph based interactive (semi-automatic) segmentation methods have emerged as a useful substitute to fully automated segmentation for many medical imaging tasks. A small amount of user input often resolves ambiguous decisions on the part of these algorithms. In this study, we propose to use graph-based active contours to segment prostate from a given magnetic resonance image (MRI). Traditional graph-based active contours are typically quite successful for piecewise constant images, but they may fail in cases where magnetic resonance image has diffuse edges, or multiple similar objects (e.g., bladder close to prostate) within close proximity. In order to mitigate these problems, we incorporate a shape prior in our graph-based prostate extraction scheme. Using real world prostate MR images from a well-known database, we show the effectiveness of the proposed method and compare it to results without the shape prior.

Index Terms— Graph Cuts, Random Walker, Magnetic Resonance Imaging (MRI), Prostate Cancer.

1. INTRODUCTION
Prostate cancer is one of the leading causes of cancer related death for men in United States and poses a growing health problem. Recently, increased life expectancy contributed a considerable rise in the reported incidence of prostate cancer. Annual incidence of prostate cancer in United States estimated to be over 220,000 cases in 2010 [1]. The most common type of prostate cancer treatment is radiation therapy. The goal of this method is to radiate a targeted area with high energy beams while avoiding damage to the surrounding organs. Having the prior knowledge about the shape of the prostate and its surrounding tissue would help the therapy to be more precise and effective. Prostate segmentation is also helpful in guiding biopsy and surgery.

Prostate extraction from MR images is a highly laborious task that is required for prostate radiation therapy and surgical guidance. Two standard segmentation approaches, manual and fully automatic segmentation, have their own disadvantages. Manual segmentation techniques require time-consuming intensive human effort that is subject to high variations from one expert to another. Fully automated methods are not successful for prostate segmentation due to diffuse edges and surrounding objects with similar intensities. Therefore, interactive segmentation [2], [3], [4], [5] with a minimal user input is an attractive option for prostate segmentation task.

Active contours method is a popular formulation of object segmentation in terms of energy minimization of certain objective functions [5]. Active contours minimize an energy function that consist of two components: external and internal energy components. The external energy component typically pulls the contour towards desired image features while the internal energy helps to smooth boundaries. An early implementation of active contours, called Snakes [6], is based on deforming an initial contour at a number of control points selected along a given initial contour. There are many variants of this method to improve robustness and stability such as gradient vector flow snakes, geodesic active contours and others. However, these methods still have the problem of converging at a local minima.

In this study, we develop a new method combining active contour and the optimization tool of graph-based methods [7], [8] (such as graph cuts and random walker) since these methods find the global minimum whereas earlier methods tend to stuck at a local minimum. Initially, we use graph cut based active contour (GCAC), and propose random walker based random contour (RWAC) for prostate extraction from MR images. A key assumption of our approach is that the desired segmentation contour is the global minimum within its a priori very rough contour which can easily be provided by the user. The size of contour neighborhood can be specified by the user for a given image. However, for medical images, these graph-based methods are insufficient as seen in Figure 1(b). The cause of this failure is often the lack of strong edges and the presence of multiple objects with similar intensities. In this study, we propose to incorporate a shape prior in graph-based active contour techniques to help us extract prostate from a given magnetic resonance image.

The main contribution of this paper is the proposal of novel methods that integrate graph-based active contour algorithms with shape priors for prostate extraction. This shape prior information helps to increase segmentation accuracy when intensity alone is not sufficient for accurate segmentation results. We present our results
for two popular graph-based segmentation algorithms, namely graph cuts and random walker.

The organization of the paper is as follows. Section 2 presents our methodology, where we briefly describe graph cuts, random walker algorithm and shape initialization technique. Section 3 shows the results of our experiments using a publicly available prostate MRI data set [9]. Finally, we offer our concluding remarks in Section 4.

2. METHODOLOGY

Let us begin this section by briefly describing two well-known graph-based segmentation algorithms; graph cuts and random walker [7], [8]. Next we present a technique to incorporate shape priors with graph-based active contours and summarize the proposed algorithms.

2.1. Graph Cuts (GC)

Boykov and Jolly introduced this algorithm for binary image segmentation [7]. The goal is to segment an object from a given image using a set of seeds (object & background) placed by a user. Specifically, let $i$ be a pixel, $V$ be the set of all pixels, and $x_i = 0$ or 1 if $i$ belongs to the background or object, respectively. Let $E^i$ be the individual pixel matching cost for pixel $i$; $E^{i,j}$ vary inversely with the difference of intensities of pixels $i$ and $j$. Then the GC cost function is

$$E = \sum_{i \in V} E^i(x_i) + \sum_{(i,j) \in E} E^{i,j}(x_i, x_j), \quad (1)$$

where $E$ is the set of neighboring pixels (edges). A combinatorial algorithm exist for minimizing $E$, based on the computing a minimum cut (maximum low) across a graph. The first term represents the cost information related to data, and second term represents a smoothness related cost. Various extension of this algorithm using shape priors has been presented in earlier studies [10]-[11]. However graph cut based active contours (GCAC) with shape priors (see Section 2.3 for details) is not presented to this date.

2.2. Random Walker (RW)

Random walker (RW) algorithm is another recently proposed seed based segmentation technique that formulates the classical segmentation problem in terms of a combinatorial dirichlet problem [8]. Similar to the GC formulation, RW algorithm is also formulated on a weighted graph, where each node represents a pixel. Graph is defined as $G = (V, E)$ with vertices $v \in V$ and edges $e \in E \subseteq V \times V$. An edge, $e$, connecting two vertices is denoted as $e_{ij}$. Let $n = |V|$ and $m = |E|$ where $|\cdot|$ denotes cardinality. A weighted graph has a value assigned to each edge called a weight denoted by $w_{ij}$.

Random walker algorithm assigns to each unlabeled node, the probability $x_i$, that a random walker starting from that node first reaches a marked node $v_i$, assigned to label $l$. The segmentation is then completed by assigning each free node to the label for which it has the highest probability, i.e., $y_i = \max_{l} x_i$. Note that the values for $y_i$, if $v_i$ is a marked node, are assigned by user-interaction. It was shown [8] that the minimization of

$$E = \sum_{e_{ij} \in E} w_{ij}(x_i - x_j)^2$$

subject to $x(v) = 1$ for $v \in F$ and $x(v) = 0$ for $v \in B$, \quad (2)

for an $n \times 1$ real-valued vector $x$, defined over the set of nodes yields the probability $x_i$ that a random walker starting from node, $v_i$, first reaches a node $v_j$ (a marked node) with label $l^*$ (set to $x_i^* = 1$), as opposed to first reaching a node, $v_j$ (a marked node), with label $l^* (set to x_j = 0)$. In this work, we extend this classical random walker algorithm to random walker based active contour (RWAC) with shape priors to obtain a better prostate segmentation. This proposed algorithm is outlined in Section 2.3.

2.3. Proposed Algorithms

To mitigate the effect of weak edges, we include a priori shape knowledge with graph-based active contours. Although shape priors were used before in [10]-[12], these studies did not consider active contour framework in their analysis. Active contours allow us to change the seed locations (automatically) in an iterative fashion while decreasing the value of cost functions.

We begin our analysis by assuming that our shape prior is a single fixed template. In Section 2.4.1, we drop this assumption to accommodate rigid transformations. Our goal will be to amend the energy function to be

$$E = (1 - \lambda)E_d + \lambda E_s, \quad (3)$$

where $E_d$ is the image (data) energy described in section on Graph cuts and Random Walker, while $E_s$ is the energy for the shape descriptor that is explained in detail in Section 2.4. With this framework, we can summarize the proposed algorithms as follows.

2.3.1. RWAC Algorithm with Shape Prior

Given a user provided initial contour surrounding the Prostate, we use the following steps.
1) Represent the image as a weighted graph with $n = |V|$ nodes and $m = |E|$ vertices
2) Dilate the current boundary using a $K \times K$ rectangular window, this operation creates an inner and outer boundary. Note that $K$ is assigned by a user, $K = 5$ is used for experiments in this paper.
3) Identify all the vertices corresponding to the inner boundary as an object seeds ($x(v) = 1$ for $v \in F$) and identify all the vertices corresponding to the outer boundary as background seeds ($x(v) = 0$ for $v \in B$).
4) Compute RW with shape prior energy Equation (3) to obtain a new boundary that separates the inner boundary from the outer boundary. 
5) Iterate Step 1-4 until boundary change is less than a threshold.

2.3.2. GCAC Algorithm with Shape Prior

Similar to the RWAC algorithm with shape prior, we follow the next steps.
1) Represent the image as a weighted graph with $n = |V|$ nodes and $m = |E|$ vertices
2) Dilate the current boundary using a $K \times K$ rectangular window, this operation creates an inner and outer boundary. Note that $K$ is assigned by a user, $K = 5$ is used for experiments in this paper.
3) Identify all the vertices corresponding to the inner boundary as a single source (object seeds) $s$ and identify all the vertices corresponding to the outer boundary as a single sink (background seeds) $t$.
4) Compute GC with shape prior energy Equation (3) to obtain a new boundary that separates the inner boundary from the outer boundary. 
5) Iterate Step 1-4 until boundary change is less than a threshold.
2.4. Shape Prior

Following the work of Freedman [4], we define a functional that allows us to match the segmented curve (c) with a template curve (e), and yet does not rely on the parametric specification of either segmented curve or the template. Here, we specify the template as a unsigned distance function (DF) whose zero level set corresponds to the template, with \( \phi : R^2 \to R \) and \( \hat{c} = x \in R^2 : \phi(x) = 0 \).

Using the idea of a level set template, the shape energy is written as

\[
E_s = \sum_{(i,j) \in E} \frac{\hat{\phi}(i) + \hat{\phi}(j)}{2}.
\]

Figure 2 presents an example of distance function where the darkest region corresponds to the zero-level set.

![Figure 2. (a) Prostate Image, (b) Distance function (DF) corresponding to the prostate contour of (a).](image)

2.4.1. Shape prior Initialization

In our prostate extraction framework, we use principal components (PCA) based method to learn a statistical shape model from a set of training images. Let us denote \( N \) manually segmented training images that are aligned by procrustes method as \( \{s_1, s_2, \ldots, s_N\} \).

The mean shape is defined as \( \hat{s}(x) = \frac{1}{N} \sum_{i=1}^{N} s_i(x) \), then the mean shape is extracted from each shape, i.e., \( \hat{s}_i = s_i - \hat{s} \). Next, we concatenate rows of \( \hat{s}_i \) to form a vector \( \eta_i \). Finally, we form a covariance matrix as \( C = \frac{1}{N-1} (\eta_1, \ldots, \eta_N) (\eta_1, \ldots, \eta_N)^T \). Next, we perform singular values decomposition on the covariance matrix. We reshape the eigenvectors obtained from singular values decomposition to the original image size. Usually, eigenshapes corresponding to the first \( L \) eigenvalues are kept while others are ignored. Hence, the shape prior is a space spanned by first \( L \) eigenvectors. In Section 3, we present examples of prostate shape found by this method for several patients. More advanced shape initialization methods available [13], however for the purposes of this paper PCA based shape initialization is sufficient as evident by the results.

3. EXPERIMENTS

In order to assess the performance of the proposed methods, we test them on a publicly available dataset [9]. We have used data set obtained from 10 patients with ground truth. Dataset consists of T2 MR prostate images from a 1.5T MR scanner. The ages of these patients range from 50 and 80.

In addition to visual results, dice coefficients and hausdorff distances with respect to expert segmentation results are used to evaluate the performance quantitatively [14], [15]. Dice measure and hausdorff distances are two common metrics used by many researchers in prostate segmentation [15]. Dice measure is defined as,

\[
\text{Dice}(A, B) = 2 \cdot \frac{|A \cap B|}{|A| + |B|},
\]

where \( A \) is the segmentation result, \( B \) is the ground truth for the tumor and the operation \( | \cdot | \) means the number of segmented pixels Haussdorff distance measures the maximum distance between two contours. For instance, for the given contours \( A = \{a_1, \ldots, a_n\} \) and \( B = \{b_1, \ldots, b_n\} \), it can be defined as follows

\[
H(A, B) = \max_{i \in \{1, \ldots, m\}} \left\{ \text{mindist}(a_i, B) \right\},
\]

\[
\max_{j \in \{1, \ldots, n\}} \left\{ \text{mindist}(b_j, A) \right\},
\]

where \( \text{mindist}(x, A) \) is defined as the minimum euclidian distance between point \( x \) and contour \( A \).

Shape space is learnt during the training stage using principal component analysis (PCA) as described in Section 2.4, the mean and eigen-shape models are used directly in the segmentation task of this experiments. Figure 3 shows the contour drawn by an expert and the shape prior contour generated by our method.

![Figure 3. Contour Initialization for several test patients. The blue contour shows the expert result, whereas the red contour is generated by our PCA scheme.](image)

Once we have the shape prior contour, we can begin the testing using the proposed methods. Initially, we compare the proposed techniques to the graph-based active contours algorithm without shape priors, as well as to graph cuts with iterative elliptical initialization algorithm of [11].

It can be easily realized that using intensities alone does not produce accurate results due to diffuse edge problem present within magnetic resonance imagery of prostate region as shown in Figure 4.(c)-(d). Similarly, graph cuts with ellipse prior (4.(g)) does not work well in our problem due to weak edges that does not result in a useful ellipse model. Table 1 provides quantitative results for 10 patients for different methods. GCAC with shape prior generally outperforms others including RWAC with shape prior for this data set. Average Hausdorff distance drops from 12.94 to 11.48, and dice measure increases from 0.83 to 0.86 when we use graph cut based techniques. Similarly, Average Hausdorff distance goes down from 16.58 to 12.58 for RW based techniques. Figure 4 illustrates the segmentation outcome for the aforementioned methods for several sample patients. (\( \lambda \) is set to 0.4 in our experiments.)

<table>
<thead>
<tr>
<th>Method</th>
<th>GCAC wo-S</th>
<th>RWAC wo-S</th>
<th>GCAC w-S</th>
<th>RWAC w-S</th>
<th>GC-Ellipse</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dice</td>
<td>0.86 ± 0.17</td>
<td>0.86 ± 0.11</td>
<td>0.86 ± 0.05</td>
<td>0.84 ± 0.09</td>
<td>0.80 ± 0.09</td>
</tr>
<tr>
<td>Hausdorff</td>
<td>12.58 ± 5.80</td>
<td>16.52 ± 7.91</td>
<td>11.48 ± 3.10</td>
<td>12.58 ± 5.80</td>
<td>15.65 ± 5.47</td>
</tr>
</tbody>
</table>

4. CONCLUSION

In this paper, we presented a novel method for prostate segmentation using graph-based techniques with shape priors. First, a PCA based
shape learning scheme is employed to learn the rough shape of the Prostate. Next, we generated an unsigned distance function (DF) of the learnt shape. We use this unsigned distance function as a priori knowledge in our graph-based active contour segmentation methods. Our results prove that an improved performance can be achieved by integrating shape term and graph-based techniques in prostate extraction with magnetic resonance imagery. We have used a publicly available data set to apply the proposed method. Compared to the existing techniques such as intensity based graph cuts, random walker, graph cuts with ellipse priors, proposed methods create more accurate prostate segmentation as shown in Table 1.

In this paper, we have compared our method with an earlier method of GC with ellipse as well as RWAC, GCAC without shape priors; and shown that the proposed method is superior to these alternatives. However, a more comprehensive comparison with methods such as [16], [15] will be the subject of our future work.

5. REFERENCES


Fig. 4. a) T2 image, b) manual (expert) segmentation results, c) GCAC without shape prior, d) RWAC without shape prior, e) GCAC with shape prior, f) RWAC with shape prior, g) Graph cuts with ellipse prior [11].