Left Atrium Segmentation for Planning Atrial Fibrillation Ablation Procedures

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Abstract. Segmentation of the left atrium is vital for pre-operative assessment of its anatomy in radio-frequency catheter ablation (RFCA) surgery. RFCA is commonly used for treating atrial fibrillation. In this paper we present an automatic approach for segmenting the left atrium, the central atrial body and its pulmonary veins from MR angiography (MRA) data sets. The left atrium segmentation algorithm is based on a region splitting and merging scheme which exploit atrium’s narrow connections to neighboring structures. The atrial body segmentation technique use level set methods which evolve under special speed functions. Finally, we also present a pulmonary vein centerline traversal scheme based on a ridgeness function. Results are presented on 20 patient MRA data-sets and results validate the robustness and accuracy of the techniques presented.

1 Introduction

One of the most common causes of deaths in patients with cardiovascular related illnesses are heart strokes and attacks. The American Heart Association reports that 15\% of all heart strokes are caused by a life-threatening condition called atrial fibrillation (AF) [1]. AF is a condition involving the left atrium of the heart. The left atrium is one of the four chambers of the heart. It receives oxygenated blood from the lungs and pumps it into the left ventricle. In a healthy adult the left atrium pumps blood into the ventricle in a regular rhythm. In AF, the left atrium quivers in an abnormal rhythm and is no longer able to pump blood into the left ventricle efficiently. This may cause possible pooling and clotting of blood in the left atrium which can lead to a stroke.

Radio-frequency catheter ablation (RFCA) has become the treatment of choice for patients suffering from AF [2]. The objective of the ablation procedure is to eliminate sources of ectopic foci by charring tissues with high radio-frequency energy. These sources are identified pre-procedurally by examining electroanatomical maps that correlate the electrophysiological characteristics with the cardiac anatomy. Medical literature indicates pulmonary venous drainages of the left atrium to be strong sources of ectopic focal activity [7]. These sources along with the atrium’s anatomy are identified and examined pre-procedurally. Several measurements such as pulmonary vein (PV) ostia diameters are also taken prior to the procedure. An automatic segmentation of the left atrium and its pulmonary veins from MRA can give a unique non-
obstructive view of the atrium’s anatomy and assist greatly in pre-planning an image-guided intervention. In addition to this, a further decomposition of the segmented atrium into the atrial body and pulmonary veins (PV) can provide automatic recognition of locations of the ostia and assist in computing their diameters.

1.1 Related Work

Relatively very little work has been reported on automated left atrium segmentation, despite the increasing popularity of RFCA in AF ablation treatment. In addition to this, to our knowledge, there is no specific literature on atrial body and pulmonary vein segmentation. The method proposed in this paper for segmentation of the central atrial body and tracking pulmonary veins is thus unique in that respect.

John et. al. [5] uses a data-driven approach for segmenting the atrium from MR Angiography (MRA) datasets. Although the method is fast and robust, it suffers from several limitations such as its inability to segment in cases where there is a non-narrow connection between a pulmonary vein and the pulmonary artery caused by a string of partial volume affected voxels. Our method is similar to the one described in [5]. An important difference is the manner in which our system can correct for over and under-segmentations using very little user-interaction. A second difference is the calculation of saddle points in [5] which is replaced with finding a point with the highest Euclidean distance value in the separating surface between any two adjacent subdivisions. This produces a more accurate estimate of the true radius of the separating surface. We also introduce novel methods for extracting the central atrial body and the pulmonary vessel center-lines which drain into the atrium.

2 Left Atrium Segmentation

The left atrium is reported to be a highly anatomically variable structure where the number and sizes of the pulmonary venous drainages can vary significantly across patients, making every RF ablation procedure unique. Variations to the right and left drainage patterns of the atrium have been documented in [3]. This high degree of anatomic variability makes the left atrium segmentation problem non-trivial.

2.1 Method

The images acquired for this study are MRA images. Prior to segmentation, unwanted structures such as bones are easily removed by subtracting the post- from the pre-MRA scans. Surrounding structures are also partly removed by using a bounding box which selects a region of interest around the left atrium, thereby excluding them as much as possible. The blood pool within the bounding box is extracted using a region-growing segmentation technique where a seed point inside the atrium is selected. The lower and upper thresholds for blood are automatically computed using the Otsu method.
The atrium is frequently connected to neighboring structures such as the aorta and pulmonary arteries through narrow regions, which are artifacts produced due to the partial volume effect. The blood pool is subdivided into regions using a scheme described below. The idea is to divide the blood pool on either sides of a narrow region. Neighboring subdivisions are later merged automatically to produce the segmented atrium. The process of subdividing the blood pool is performed in three steps: 1) Computing the Euclidean distance transformation of the image. 2) Finding local maxima on the EDT map. 3) Determining subdivision membership for each voxel in image.

In the first step we compute the Euclidean distance transformation (EDT) of the binary blood pool. The next step is to compute the local maximum points on the EDT map. We use a 26-voxel neighborhood, for calculating local maxima. Next, we determine each voxel’s subdivision membership. Starting from a voxel we search along the path of the maximum ascent until we reach a local maximum. The voxel belongs to the subdivision that is centered by this local maximum. In this way each voxel converges to a local maximum, and each local maximum produces unique subdivisions containing voxels which converge to it. Subdivisions are identified by their centers which is a local maximum. This is analogous to a Voronoi diagram where a Voronoi cell is similar to a subdivision. Fig. 1(ii) shows how the entire blood pool is subdivided using the subdivision scheme described above.

Once subdivisions are produced, they are automatically merged using a pre-defined criterion which exploits the anatomy: physically the left atrium is only connected to the left ventricle through the mitral valve. However, as described earlier, in MRA images, due to the partial volume effect the subdivisions on either sides of narrow regions connecting the atrium to neighboring structures are prevented from merging, whilst allowing other regions to merge.

Consider the radiuses of two neighboring subdivisions and which are separated by a separating surface \( s \) (Fig. 1(i)). The radius of a subdivision is the Euclidean distance value of its local maximum. Assuming that \( a \) and \( b \) are the radiuses of two neighboring subdivisions with the separating surface radius denoted by \( p \). A merging criterion can be described in terms of a merging value \( T \) which is defined as:

\[
T = \min(a, b) - p
\]

The merging value can be controlled using a user-defined threshold. The merging criterion allows any two adjacent subdivisions to be merged when their merging value
satisfy a threshold. In this way, the radius of the separating surface at a narrowing will have a smaller radius compared to the radiiuses of the adjacent subdivisions, thus yielding a large merging value. Small merging values are expected at non-narrow connections. This way, selecting an appropriate threshold value will thus stop the merging process at possible narrowings. The merging process starts from a user-selected seed point, preferably located close to the centre of the atrium. The subdivision containing the seed point is our seed subdivision. Similar to a region-growing approach, all subdivisions connected to the seed subdivision are merged on the condition that they fulfill the merging criterion. At the end of the merging process the resulting merged subdivisions is the segmented atrium separated from the rest of the connected structures.

3. Atrial Body Segmentation

In image-guided RFCA it would be ideal if a patient’s left atrium anatomy can be automatically classified. Further quantifying ostium diameters can help select the right catheter size. Solving this problem computationally would require an automatic labeling scheme for atrium’s primary components, i.e. the atrial body and the pulmonary veins. In this section, we present a segmentation scheme for the central atrial body.

3.1 Method

The method is based on evolving surfaces using level set methods [6]. The idea is to use a propagating front to stop at the atrial body edges, except in places where the atrial body meets the pulmonary veins where it is stopped using the combined effects of the speed image and a curvature constraint. In a level set method framework, the evolving surface is implicitly defined as the zero level set of a higher dimensional distance or level set function \( \phi \). Consider an evolving surface with position denoted by \( \tilde{s} \) and a speed function \( F \) which gives the speed of the surface in its normal direction. The surface \( \tilde{s} \) is embedded in a higher dimensional function \( g \), the zero level set of which is given by the equation:

\[
\phi(\tilde{s}, t) = 0
\]

Then, by the chain rule, an evolution equation for the evolving surface is obtained:

\[
\phi_t + F|\nabla \phi| = 0
\]

This is an initial value partial differential equation of the Hamilton-Jacobi type which can be solved using various numerical schemes [6]. The choice of speed function \( F \) is crucial for segmentation as it determines the convergence speed and the accuracy of the final atrial boundary positions. A simple speed function can be constructed which stops the level set at object boundaries:

\[
F(x, y, z) = e^{-|\nabla \phi|}
\]
Where $\sigma$ denotes the scale at which the image gradient $\nabla I$ is calculated. In noisy images, however, this is not adequate as an unsupervised propagating front can easily diffuse into the PV drainages connected to the atrial body. Our choice of the speed function restricts the level set to remain within the atrial body and stops it from propagating further into PV. The speed function can be split into two components:

$$ F = F_A + F_G $$

where $F_A$ is the advection term and is independent of the propagating front’s geometry. The second term $F_G$ depends on the geometry of the front, such as its local curvature. Eq. 5 under the influence of $F_A$ and $F_G$ now becomes:

$$ \phi + F_A |\nabla \phi| + F_G |\nabla \phi| = 0 $$

We use the Euclidean distance transform function as the advection speed term. It produces a reasonable speed function which can cause the propagating front to grow within the atrial body (high EDT value) and stop near the boundary of the structure (an EDT value of 0 at the boundary). It also causes the front’s speed to decelerate at the mouth of a PV (i.e. ostium) where at such locations it may encounter small values of EDT due to a narrowing. However, the EDT alone is not sufficient enough to stop the front from propagating into PV. To this end we use the second speed term $F_G$ in Eq. 5 to impose a curvature constraint on the front’s geometry. The curvature is computed using:

$$ \kappa = \nabla \cdot \frac{\nabla \phi}{|\nabla \phi|} $$

A speed term which moves proportional to the front’s curvature can now be defined, where $\varepsilon$ is the curvature constraint control parameter:

$$ F_G = 1 - \varepsilon \kappa $$

Thus, the propagating front driven by the level set Eq. 6 with the above mentioned speed functions can segment the atrial body but only reasonably well; we observed that the front stopped prematurely close to the atrial body wall. This is caused by the EDT-driven advection term which approaches values close to zero near the atrial boundary. However, this first step is yet important since we acquire a good approximation of the atrial body’s shape. The segmentation is next further improved by pipelining it into a second level set scheme. The segmentation obtained in the previous step is used as an initial contour in this second step. The propagating front uses a simple image gradient based advection term such as in Eq. 4 together with a relatively high curvature constraint. These two factors cause the front to restrict itself to an initial shape and to propagate further towards atrial boundaries. Note that although the advection term allows the front to leak into the PV this time, it is yet prevented to do so because of the high curvature constraint. It may also be worth noting that noisy images are required to be smoothed using an anisotropic diffusion filter prior to deriving the speed images required for front propagation.


4 Pulmonary Vein Centerline Tracking

We have also developed a technique for tracking the pulmonary vessels which drain into the left atrium. The pulmonary vessels are of particular relevance in the context of AF ablation procedure as these frequently contain locations of an ectopic discharging focus [7]. Also tracking of each pulmonary vessel drainage reveal which of the documented [3] anatomical arrangement is present.

4.1 Method

Our technique relies on the extraction and traversal of centerlines of tubular structures. Without loss of generality, we assume that pulmonary vessels appear brighter than the background in MRA images. Since the flow of blood is fastest along the vessel centerline, voxels in this region are the brightest. Based on this a-priori information, a pulmonary vessel segment in MRA images can be assumed to be a tubular object with high intensity along its centerline. This high intensity centerline is also called an intensity ridge. A ridge can be generalized as a 1D maximum convexity height ridge of an $N$-D surface. To enhance this intensity ridge, a Gaussian blur with a width which matches that of the vessel diameter is required. Also, since pulmonary vessels have different diameters, using a Gaussian blur at varying widths employs a multiscale approach. We use Frangi’s vesselness filter [4] to measure vessel diameters.

Our goal is to traverse along these intensity ridge points starting from a seed point, which is assumed to be not located on the ridge. We employ a ridgeness measure for every point on the image. Consider a continuous image function given by $I(x, y, z)$. If the intensity value is considered to be the height from zero, ridge points are points where the image has a local maximum in the direction of the principal curvature of $I(x, y, z)$. Using this criterion, the second-derivative information at a point can be used to distinguish ridge points. The Hessian matrix, which captures second derivatives in higher dimensions, can be analyzed to determine ridgeness at a point. It is well known that for a point to be on a 1-D ridge of an $N$-D surface, $N-1$ eigenvectors of the Hessian $H$ of $I$ at $(x, y, z)$ have negative eigenvalues. Thus, given $\lambda_1, \lambda_2, \lambda_3$ are ordered eigenvalues of $H$ with $|\lambda_1| \leq |\lambda_2| \leq |\lambda_3|$, at a ridge point we must have:

$$\lambda_1 \leq \lambda_2 < 0 \quad (9)$$

The respective eigenvectors $v_1$ and $v_2$ are assumed to be directions which are normal to the ridge. Based on this notion, also at a ridge point the projection of the image gradient onto the directions normal to the ridge must be zero, i.e.

$$v_1 \cdot \nabla I = 0 \quad \text{and} \quad v_2 \cdot \nabla I = 0 \quad (10)$$

Using Eq. 10, a ridgeness function $J(x, y, z)$ is defined over the image’s domain as:

$$J(x, y, z) = (v_1 \cdot \nabla I)^2 + (v_2 \cdot \nabla I)^2 \quad (11)$$
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**Fig. 2.** (i) An ideal bright 3D line with radius = 5.0 blurred using a Gaussian kernel of width =5.0. (ii) The Ridgeness function computed for the ideal 3D line

$J$ is minimal on a 1-D height ridge point of a 3-D surface. In other words, at pulmonary vessel centerlines we can expect $J$ to be close to 0. Starting from a seed point, we move the seed point to a ridge point using a minimization scheme. To this end, we employ a simple hill-climbing minimization method whereby we follow along the direction of maximum descent starting from the seed’s 26-neighborhood. We use cubic B-splines to estimate $J$ at sub-voxel locations. Once we are at our first ridge point $x_0$, we begin our ridge traversal process. Ridge traversal is an iterative process whereby at each iteration $i$ we seek to move to the next ridge point $x_{i+1}$ from $x_i$. Since the third eigenvector $v_3$ approximates the vessel tangent direction, and we are at a ridge point, it is most feasible to move a small number steps in the direction of $v_3$ which brings us to a point which may not necessarily be on the ridge. However, we can easily get back on the ridge by minimizing our ridgeness function $J$ once again at that point.

Due to the presence of image noise, normally more than one seed point is required to extract an entire vessel branch. To this end, we propose an automatic seed generation process. Using Frangi’s multi-scale vessel enhancement filter [4], we measure the vesselness for each voxel in the segmented atrial image, except for the atrial body. We threshold the vesselness response above a certain response $\tau$ and randomly select 5% of the voxels to be potential seed points. This way we only select points which have high vesselness and by virtue of vesselness are expected to lie very close to, or on the vessel ridge. Automatically selecting seed points which lie close to the ridge reduces the ridge finding and traversal processes significantly.

5 Results

We have tested our left atrium segmentation technique on 20 patient MRA datasets. The datasets acquired were diverse in terms of the anatomy of the left atrium and its pulmonary veins. One of the datasets had an abnormal enlarging of the left atrial body (Fig. 3a), and one of them had an unusual left drainage where the two left pulmonary veins joined into one vessel (Fig. 3c). The proposed technique was robust against these cases and all cases were segmented successfully. The segmentation results were evaluated by an expert clinician by overlaying the segmentation on the original MRI and noting the differences.
Fig. 3. Marching cubes iso-surface reconstruction of the segmented left atriums of 10 patient MRA datasets. Note the variation in shape, size and anatomy of the atrium across patients.

Fig. 4. Single slice images of the segmented atrial body (white) overlaid on top of the segmented atrium (grey).

Fig. 5. (i) A pulmonary vessel drainage circled (ii) Inside the vessel drainage (iii) The tracked centerline of the pulmonary vein.

References