Left Ventricle Segmentation by Dynamic Shape Constrained Random Walks

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***Abstract*— Accurate and robust extraction of the left ventricle (LV) cavity is a key step for quantitative analysis of cardiac functions. In this study, we propose an improved LV cavity segmentation method that incorporates a dynamic shape constraint into the weighting function of the random walks algorithm. The method involves an iterative process that updates an intermediate result to the desired solution. The shape constraint restricts the solution space of the segmentation result, such that the robustness of the algorithm is increased to handle misleading information that emanates from noise, weak boundaries, and clutter. Our experiments on real cardiac magnetic resonance images demonstrate that the proposed method obtains better segmentation performance than standard method.**

I. Introduction

Cardiovascular disease is the leading cause of death in the United States and Western world [1] albeit that mortality has been declining over the years owing to the development of new cardiac imaging technologies. To help in the diagnosis of disease, physicians are interested in identifying the heart chambers, the endocardium and epicardium, and measuring the change in ventricular blood volume and wall thickening properties over the cardiac cycle. The left ventricle (LV) is of particular interest since it pumps oxygenated blood out to distant tissue in the entire body. There are a number of techniques for clinical diagnosis of heart diseases and conditions: Both magnetic resonance (MR) and computer tomography (CT) imaging provide the physician with excellent quality images which allow a detailed analysis of the organ.

The motivation for image segmentation is to quantitatively analyze global and regional cardiac function from MR or CT images. This is done by extracting clinically-meaningful parameters – such as ejection fraction (EF), myocardium mass (MM), and stroke volume (SV) – from these segmented images. Calculations of these parameters depend on accurate delineation of the endocardial and epicardial contours of the LV. To remove bias and variance of manual segmentation, and obtain reproducible measurements, an automatic segmentation technique is desirable. Over the years, many methods had been developed to address the problem of LV segmentation from cardiac sequences [2, 3].

Among the existing image segmentation techniques, several methods benefit from mapping the image elements onto a graph. The segmentation problem is then solved in a spatially discrete space by efficient tools from graph theory. One of the advantages of formulating the segmentation on a graph is that it might require no discretization by virtue of purely combinatorial operators and thus incur no discretization errors. Recently, two graph-based methods – graph cuts [4, 5] and random walks (RW) [6, 7] – have been successfully employed in LV segmentation. Compared to the graph cuts, the RW algorithm does not suffer from the "small cut" problem and extends naturally to an arbitrary number of labels. The RW algorithm has been successfully applied in cardiac data and brain image segmentation [6, 7, 8, 9], and demonstrated good performance of weak boundary detection, noise robustness, and the assignment of ambiguous regions.

Nowadays, segmentation of the LV still remains a challenging problem due to its subtle boundary, occlusion, and image inhomogeneity. In order to overcome such difficulties, we aim to solve the challenging issues encountered in the LV segmentation due to subtle boundary, occlusion and image inhomogeneity. We propose a improved segmentation method by incorporating a dynamic shape constraint into the weighting function of the RW segmentation algorithm. The dynamic shape constraint is formulated by a fitted circular function from the boundary points of the RW segmentation, which leads to an iterative approach that updates an intermediate result to the desired solution. The shape constraint restricts the solution space of the segmentation result such that the robustness of the algorithm is increased to handle misleading information that may arise from noise, weak boundaries, and clutter. The effectiveness of the proposed approach is verified by experimental results on real CMR images from the Cardiac Segmentation Challenge [10].

The rest of this paper is organized as follows: Section II reviews the related techniques and presents the proposed image segmentation approach. The experimental results of the proposed approach are reported in Section III. Finally, the conclusion is given in Section IV.

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978-1-4244-7929-0/14/$26.00 ©2014 IEEE

II. METHODOLOGY

A. RW for Image Segmentation

Let us define the notions for a graph before introducing the RW algorithm. A graph consists of a pair $G = (V, E)$ with vertices (nodes) $v \in V$ and edges $e \in E$. An edge, e, spanning two vertices, v_i and v_j, is denoted by e_{ij}. A weighted graph assigns a value to each edge called a weight. The weight of an edge, e_{ij}, is denoted by $w(e_{ij})$ or w_{ij}. The degree of a vertex is $d_i = \Sigma w_{ij}$ for all edges e_{ij} incident on v_i. In order to interpret w_{ij} as the bias affecting a random walker's choice, it is required that $w_{ij}>0$. The following will also assume that the graph is connected and undirected, i.e., $w_{ij}=w_{ji}$.

The RW [6, 7] is an interactive segmentation method that is formulated on a weighted graph to assign a label to each pixel on an image. Each edge on the graph is assigned a real valued weight defined as:

$$w_{ij} = \exp(-\beta(g_i - g_j)^2) \tag{1}$$

where g_i is the image intensity at pixel i and β is a free parameter. This weight can be taken as the likelihood that a random walker will go across that edge. As a consequence, the label of a pixel is given by the seed point that the random walker first reaches. The theoretical basis of RW is an analogue of the discrete potential theory on electrical circuits, as discussed in [7]. The solution of RW probabilities has been found to be the same as minimizing a combinatorial Dirichlet problem:

$$D[x] = \frac{1}{2}\sum_{e_{ij}\in E} w_{ij}(x_i - x_j)^2 \tag{2}$$

Minimizing $D[x]$ is equal to solving the harmonic function that satisfies the boundary condition, which can be set by letting the seed point value be unit. *Eq.(2)* has an identical form to the graph cut function. However, RW has a higher likelihood of reaching the seed with the least steps, and thus avoiding segmentation leakage and shrinking bias. Sinop et al [11] unified the graph cuts [4, 5] and RW [6, 7] into a general framework, which is based on the minimization of *lq* norms.

The summary of the RW algorithm is described as follows:

1) Obtain a set of marked (or labeled) pixels with K labels (where K is the number of the labels), either interactively or automatically.
2) Build the lattice, which is composed of nodes and edges. RW treats an image as a purely discrete object – a graph with a fixed number of vertices and edges.
3) Choose a weighting function, which maps a change in image intensities to edge weights. The typical Gaussian weighting function is given by *Eq.(1)*
4) Solve each label by
$$L_U x^s = -B^T m^s \tag{3}$$
where x_s $(0 < s \le K)$ represents a vector of probabilities for each node to reach to the seeds with label s. We refer to [7] for the definition of L_U, B^T and m^s.
5) Assign to each node the label according to the maximum probability $\max_s(x_i^s)$, and the final segmentation can be obtained.

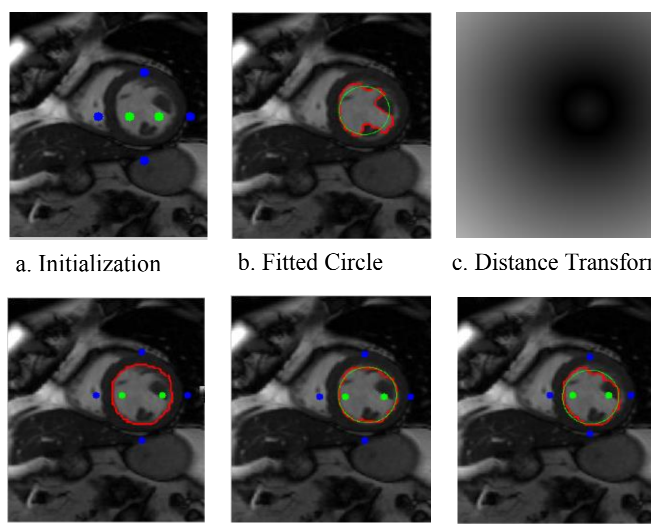
B. RW Related Problems

The RW algorithm has been successfully applied in cardiac data and brain image segmentation [6, 7, 8, 9], but it is worthy to note that the seed selection is the key step for the RW implementation. Segmentation result is extremely sensitive to the location of the seeds. Improper position of seeds will lead to false segmentation results.

As illustrated in Section III later in this paper, we can observe several problems related to the RW for LV segmentation: 1) the segmentation result by RW is not constant but sensitive to the location of the seeds; 2) it is difficult to correctly initialize the seeds location without prior knowledge of the image, especially when papillary muscle exists inside or adjacent to LV cavity; and 3) it is also difficult to automatically segment the papillary muscle into the LV cavity by using only intensity information due to the large intensity variance. In such a scenario, inclusion of shape information assumes immense significance in LV segmentation. As the LV cavity appears as a circular shape in most CMR images, this inspires us to incorporate the circular shape information into the algorithm to improve the performance of the RW segmentation.

C. The Proposed Approach

We propose to formulate the shape information as the dynamically fitted circle of the segmented contour from the previous RW segmentation iteration. Such that avoid the requirement of any prior shape training, and handle the circular shape varying at the same time.



a. Initialization b. Fitted Circle c. Distance Transform

f. 3rd iteration result e. 2nd iteration result d. 1st iteration result

Fig.1. Step-by-step illustration of the proposed segmentation approach, refer to the text for the detailed description.

As illustrated in Fig.1, the proposed approach for the LV segmentation on a given CMR image can be summarized as follows:

1) Initialize the foreground seeds (green-colour points) and background seeds (blue-colour points), either interactively or automatically, as shown in Fig.1a.
2) Segment the image by using RW algorithm with the initialized seeds, and fit a circle by using the segmented LV boundary points. The segmented LV boundary and the fitted circle are indicated by red-colour and green-colour contours, respectively, as shown in Fig.1b.
3) Obtain the distance transform map of the fitted circle, as shown in Fig.1c.
4) Incorporate the circular shape information into weighting function of RW by

$$w_{ij} = w_{ij}^{o} + \alpha w_{ij}^{s} \tag{4}$$

where w_{ij}^{o} (the intensity feature) is the weight from the original image, and w_{ij}^{s} (the shape feature) is the weight from the distance transform map of the fitted circular shape, and α is the free parameter to adjust the weight of the intensity feature against the shape feature.
5) Refine the seed locations in terms of the fitted circle center. This is done by re-segmenting the image by using the RW algorithm with the updated weighting function. A circle is then fitted over the re-segmented LV boundary points. The refined seeds are indicated by green and blue colour dots, the segmented LV boundary is indicated by red-colour contour, and the fitted circle is indicated by green-colour contour, as shown in Fig.1d.
6) Repeat Steps 3 to 5 until the maximum iteration is reached or the circularity of the segmented contour exceeds the specified level. For illustration, the segmented LV boundaries from the 2nd and 3rd iterations are shown in Fig.1e and Fig.1f, respectively.

If the segmentation is performed on a sequence of images, e.g., one cycle frames (typically 20-25 images), the segmented result of the current frame can be propagated to the next adjacent frame for seed initialization. The center pixel of the adjacent image frame is computed using the segmented LV cavity of the previous frame. The foreground and background circular points/seeds can then be defined and used as the initialization of the RW algorithm to segment the adjacent image. The additional steps of the proposed approach for LV segmentation on a sequence of frames can be summarized as follows:

7) Propagate the segmented contour of the current frame to the next adjacent frame, and initialize the foreground and background seeds.
8) Repeat Steps 2 to 6 to get the segmentation result for this adjacent frame.
9) Repeat Steps 7 to 8 until all the frames in the sequence are segmented.

III. Experimental Results

To evaluate the performance of the proposed approach on cardiac LV cavity segmentation, we apply it to real CMR images from the Cardiac Segmentation Challenge [10]. In all examples, we fix the free parameter $\beta=90$ for *Eq.(1)* and $\alpha=0.5$ for *Eq.(4)*. The routine used in this study is modified based on the MATLAB source code from [12]. In all examples, the green dots indicate the foreground seeds, blue dots indicate the background seeds, and red (and/or green) curves indicate the segmented LV cavity boundaries.

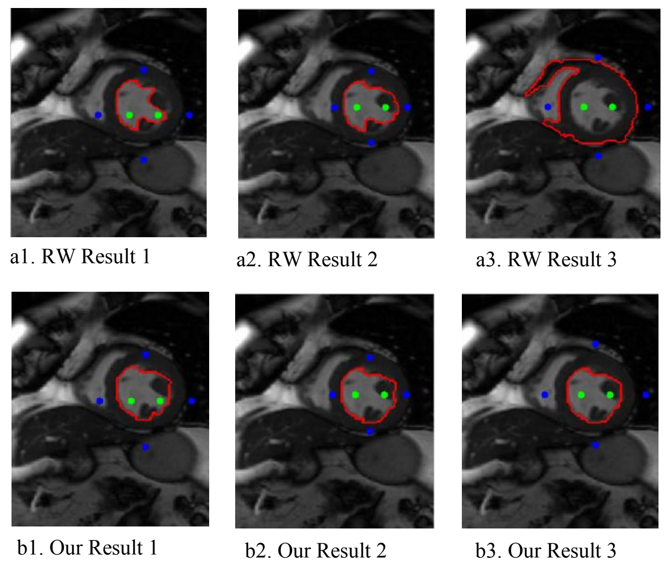


Fig.2. Segmentation comparisons of standard RW and the proposed approach on an image frame (frame #0148, patient #01) with three different locations of seeds

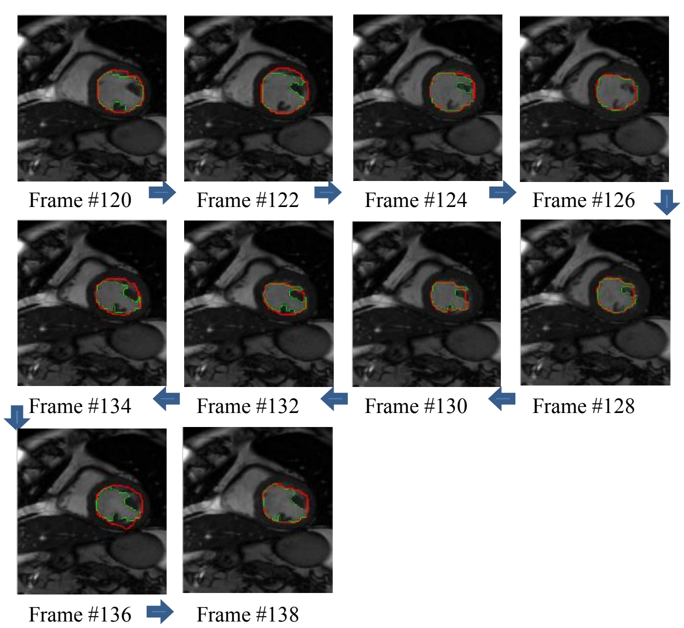


Fig.3. Segmentation comparisons of standard RW and the proposed approach on a sequence of image frames (frames #0120 to #0139, patient #01, only show the frames with even number), green-colour contours obtained by standard RW while red-colour contours from the proposed approach.

We first compare the performance of the proposed approach to the standard RW for segmentation of a CMR image (frame #0148 of patient #01) from the RV Challenge website. The purpose is to demonstrate that the proposed approach is not sensitive to the seed locations as suffered by the standard RW. For the image in Fig.2, we initialize the foreground and background seeds with slightly different locations. For different seed locations, the standard RW algorithm yields different segmentation results, as shown in the first row of Fig.2, which is in accordance with the discussion in Section II. In contrast, our proposed approach achieves much better results than those of the standard RW. More importantly, the results of our proposed approach are nearly the same regardless of the seed locations, as shown in the second row of Fig.2.

We further demonstrate the effectiveness of our proposed approach on the segmentation of a sequence of images from the RV Challenge website. The image size is 256x216, with 20 images per cardiac cycle. The testing is performed on patient #1, frame #0120 to frame #0139 (one cardiac cycle). The segmentation is started from frame #0120 and propagated to the subsequent frames one-by-one until all the frames are segmented. The final segmented results are shown in Fig.3, where the green-colour contours are obtained by standard RW algorithm, while the red-colour contours are from the proposed approach. It can be observed from the figure that the segmented LV cavity boundaries from the standard RW are seriously distorted by the papillary muscles in most of the images. In contrast, our proposed approach achieves much better results in that the segmented contours conform closely to the actual boundaries of the LV cavity even though papillary muscles are adjacent to or fall inside the LV region in some frames.

IV. CONCLUSION

Cardiac image segmentation plays a crucial role and allows for a wide range of applications, including quantification of volume, computer-aided diagnosis, localization of pathology, and image-guided interventions. It is the object of the present work to provide an image segmentation approach for the automated extraction of the LV cavity in cardiac magnetic resonance (CMR) images, in order to assist the cardiologists in the detection and diagnosis of cardiovascular disease. Poor edge information and large within-patient shape variation of the different parts necessitates the inclusion of prior shape information. In this work, the implementation is achieved by incorporating a dynamic shape constraint into the weighting function of the RW segmentation algorithm, with the shape constraint formulated by the fitted circle function from intermediate segmentation result. The experimental results have shown that the integration of the dynamic shape constraint into the RW image segmentaton achieves a better segmentation performance as compared to the original method.

ACKNOWLEDGMENT

This work was partially supported by SERC Biomedical Engineering Programme Grant (BEP 132 / 148 / 0012), Singhealth Foundation (SHF / FG453P / 2011), Goh Cardiovascular Research Grant (Duke-NUS-GCR / 2013 / 0009), and BMRC Research Grant (14 / 1 / 32 / 24 / 002).

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