Dual Cavity Segmentation of Left and Right Ventricles in Cardiac MRI by Guided Random Walks with Registration

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***Abstract*—In this paper we propose a new method for accurate segmentation of the left and right ventricles simultaneously in cardiac magnetic resonance images. Our approach is based on guided random walks and registration in order to efficiently exploit the prior shape knowledge. The contribution of the proposed method is in using registration of the pre-segmented data and then guided random walks segmentation that allows covering the variations of dual cavity hearts (left and right ventricles) without needing a huge dataset. The proposed framework starts with some manually placed seeds which are used for initial estimation of the size of the heart in the input image and also provides the boundary conditions for the guided random walks. Then, the model is registered to the input image which will be segmented by the help of the model through solving a system of linear equations. The registration and segmentation will be repeated until the model and the input images are completely aligned and the optimal segmentation is achieved. For validation the proposed method is applied to 125 cardiac MR images including normal cases as well as patients. The promising experimental results (average Dice=86.43%) illustrate the benefits of our approach for dual cavity segmentation of the left and right ventricles.**

***Index Terms*— segmentation by retrieval, Random walks, Registration, left and Right ventricle segmentation, cardiac cine MRI**

I. Introduction

Cardiovascular diseases (CVD) are the most common causes of death in the developed world and modern societies [1]. Segmentation of the right and the left ventricles provide valuable information about the functionality of the heart. Important diagnostic indices are computed from the segmented right and left ventricles. Some of these indices are end systolic and end diastolic volumes (ESV, and EDV), stroke volume (SV=EDV-ESV), and ejection fraction (EF=SV/EDV). The ejection fraction of the left ventricle (LV) is an important indicator of heart failure, and myocardial infarction while computed ejection fraction of right ventricle (RV) is used to diagnose dysplasia, cardiomyopathy, and pulmonary artery diseases like pulmonary hypertension and pulmonary artery stenosis [2].

Simultaneous segmentation of the right and the left ventricles has recently raised attention as it allows not only inspecting the performance of each ventricle but also their synchronous function. Manual segmentation of the left and right ventricles is tedious, time consuming and error prone. Several automatic and semi-automatic approaches have been published with the focus on left ventricle segmentation. In automatic approaches the location of the heart is mostly determined through of the Hough transform [3]-[5] or Fourier transformation of the image sequence [5], [6]. User interaction is use for determining for localizing the heart in semi-automatic methods. Among different approaches are active contours [7]-[10], statistical active shape and appearance models [11]-[14], clustering [15], [16], and atlas-based segmentation [17]-[19]. Eslamiet al. proposed a manifold of approaches with Mumford-Shah formulation for left ventricle segmentation [20] .In comparison with the LV, segmentation of the RV is more challenging due to its thin myocardial layer and high shape variation. [21], [22].Recently graph-based methods have been proposed for segmentation that allows arbitrary segmentation of any image given sufficient user interaction (Boykov&Funka-Lea 2006) (Grady 2006) [23], [24]. Later prior knowledge was introduced to graph based approaches as energy terms with priors and spatial random walker energy terms [24], [25]. By additional prior knowledge into graph-based algorithms such as topology-priors, boundary information, appearance, shape we refer to the recent work of Grady (Grady 2012) [26] And prior knowledge was introduced by extending the fundamental potential energy function into random walks we can see improve convergence properties for iterative solvers [27].

In this paper we modify the recently proposed method of guided random walks by Eslami et al. [27] in order to simultaneously segment the left and right ventricles. In [27] guided random walks is proposed by incorporating prior shape knowledge in terms of pre-segmented data into the random walks formulation. Guided random walks successfully applied to the segmentation of the left ventricle in [27] relying on a large pre-segmented dataset. However, because of the more complex geometry of dual cavity hard (the right and left ventricles), guided random walks segmentation requires a large database that contains the various shapes of the normal subject and

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different diseases heart. Instead we propose using registration of the pre segmented data and the input image.

This paper is organized as follows: The theoretical background and formulation of the proposed methods is discussed in details in section II .The experimental results from clinical data are reported in section III and the results are discussed. Finally, the paper is concluded in section IV.

II. METHOD

We propose our method of segmentation based on graph representation of the image in which nodes $\{n\}$ represent the pixels of the image and edges $\{e\}$ characterize the connectivity of the pixels that is weighted by their intensity similarity.In this paper, neighbourhood is defined with 4-connected topology for constructing the graphs from the image.Implementation is easier for 4-connected topology while the 8-connected topology has higher computation complexity but does not improve the results significantly.

Pixels are represented by nodes graph representation of the image consists of nodes n Starts with manually putting some foreground seeds on the left and right myocardium, and background seeds inside the cardiac cavities and outside of the heart.Let x_i be the likelihood of pixel i and indicate theforeground if likelihood of pixel$x_i > 0.5$ (belong to either right or left myocardium), the left and right ventricles can be segmented by minimizing the following cost function.

$$E(X) = \frac{1}{2}\sum_{c_{ij} \in \mathcal{C}_{I:I}} w_{ij}\left(x_i - x_j\right)^2 + \frac{\gamma}{2}\sum_{c_{ij} \in \mathcal{C}_{I:R}} \omega_{ij}\left(x_i - b_j\right)^2 \tag{1}$$

$$w_{ij} := \begin{cases} \exp\left(-\beta\left(I_i - I_j\right)\right) & \text{i, j connected} \\ 0 & \text{O.W.} \end{cases} \tag{2}$$

$$\omega_{ij} := \begin{cases} \exp\left(-\alpha\left(I_i - R_j\right)\right) & j = i \\ 0 & \text{O.W.} \end{cases} \tag{3}$$

whereα, β and γ are constant positive parameters andx_i,x_j are the likelihood of pixels iand j, respectively. The intra-image weight w_{ij} in eq. (2) is defined zero for unconnected pixels and those connected pixels with high intensity contrast. By minimizing the cost function in eq. (1), similar likelihoods will be assigned to those connected pixels with similar intensities due to the first term in eq. (1) as their corresponding weight in eq. (2) is large. With large weights (w_{ij}) eq. (1) is minimized when $\left(x_i - x_j\right)^2$ is small and the likelihood of the pixels are similar.

The second term in eq. (1) involves prior knowledge in the problem formulation and its effect is controlled by the constant positive parameter γ . The employed prior knowledge here is in the form of pre-segmented image including raw image R and corresponding binary label b in which $b = 1$ indicates the left and right ventricles myocardium and $b = 0$ determines the background. The inter-image weight function ω_{ij}in eq. (3) is defined to be large for the corresponding pixels with similar intensities in the input image (I) and the raw image (R). The rationale behind the second term of Eq. (1) is that when the input image and the model are roughly registered then two pixels most probably belong to same region (myocardium or background) if they have similar intensities. Therefore, for the pixels i and j with similar intensities in the two images ω_{ij} is defined to be large in eq. (3) so their likelihood x_i and $b_j$become similar. It is shown in [27] that the cost function in eq. (1) can be minimized by solving the set of linear equations:

$$(L_U + \gamma A_U)x_U = \gamma\Omega_B^T b_M + \gamma\Omega_U b_U - L_B^T x_M + \gamma A_B^T x_M \tag{4}$$

where x_U is the unknown likelihood of unmarked pixels and x_M the likelihood of the seed points which is zero for the background seeds and one for the foreground seeds at myocardial regions. Vectors b_U and b_M are the predefined likelihoods of the corresponding points from the binary image (b).

The matricesL, A, and Ω are sparse and defined as:

$$\Omega_{ij=}2\omega_{ij} \tag{5}$$

$$L_{ij} = \begin{cases} L_i & j = i \\ -2w_{ij} & e_{ij} \in C_{I::I} \\ 0 & e_{ij} \notin C_{I::I} \end{cases} \quad L_i = 2\sum_{e_{ij} \in c_{I::I}} w_{ij} \tag{6}$$

$$A_{ij} = \begin{cases} A_i & j = i \\ 0 & \text{o.w.} \end{cases} \quad A_i = \sum_{e_{ij} \in c_{I::R}} \omega_{ij} \tag{7}$$

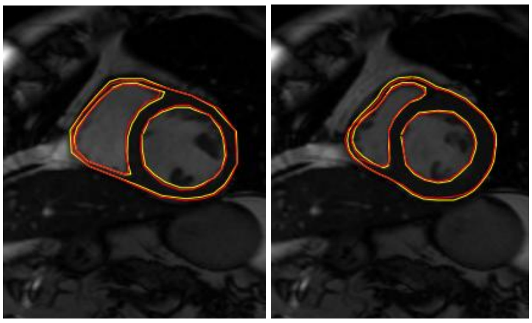
Theinitial step of manual seeding can also be performed automatically by exploiting automatic techniques of heart localization and then extracting the myocardial region based on the intensity histogram of the region of interest. However, in this paper we focus on the segmentation method and the seedswere placed manually at the beginning of our proposed framework of segmentation. Once the seeds are placed a region of interest of the size of $140\times140\times10$ is extracted around the left and right ventricles. The foreground seeds give a rough estimation of the size of the heart which is used for initial registration of the model to the input image. Fig. 2 shows the flowchart of the proposed algorithm.

Maximum performance can be achieved when the input image and the model are aligned. Therefore the proposed framework starts with a roughly aligned pre-segmented image to incorporate prior knowledge and iteratively improves the segmentation by registering the pre-segmented image to the input image. Iterations continue until further improvements are not achieved or maximum iteration is reached.

III. EXPERIMENTAL RESULT

The proposed method is applied to clinical data including125 short-axis cardiac cine MR images for evaluation. Images were acquired at 20 time points along the cardiac cycle and the heart were images at 14 slides at each frame. In total, 24480 2D images are segmented, and the segmented left and right ventricles are compared with manual segmentations by an expert. Both endocardial and epicardial borders were traced by the expert in order to provide ground truth for validation of the proposed segmentation.

In this paper we realized there are related between the outliers in our experimental results and to either serious miss-registration or absence of matching Model in the training set.



(a) (b)

Figure 1. :Segmentation result by the proposed method (Red) and manually traced endocardium and epicardium (Yellow) at (a) end of diastoleand (b) end of systole.

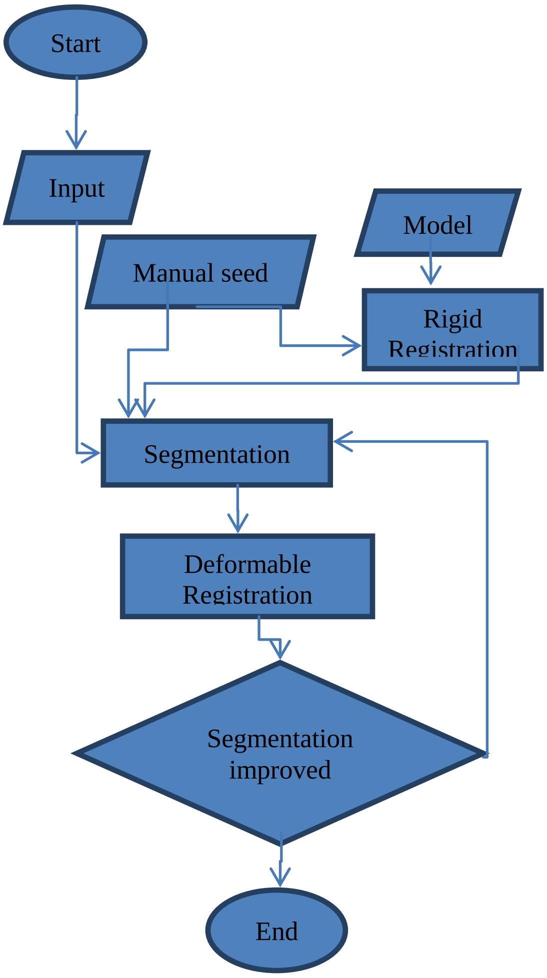


Figure 2. Flowchart of the proposed method

Performance of the proposed method can be qualitatively compared with the manual tracing of the expert in Fig. 1. The extracted endocardial and epicardial borders from the proposed method is red and the yellow contours are the borders delineated by the cardiology expert. It can be inferred from the image that the extracted borders are fairly close to the manual segmentation even in the vicinity of the lung where there is not a good contrast between LV myocardium and lung.

In addition to the qualitative result, the proposed method is quantitatively evaluated by computing the segmentation error in terms of Dice metric [9]. The Dice coefficient indicates the similarity between the extracted myocardium and manual segmentation based on their intersection. Let O_e be the extracted myocardium of the left and right ventricles and O_m the manually segmented myocardium. The Dice coefficient (D) is defined as the cardinality of the intersection of the two regions divided by the sum of their cardinalities.

$$D(O_m, O_e) = \frac{2A(O_m \cap O_e)}{A(O_m) + A(O_e)} \tag{8}$$

where$A(O)$ denotes the area of the object O.

TABLE I. ACCURACY OF THE PROPOSED METHOD IN DICE METRIC ($\mathcal{D}$M%)

LV Endocardium	LV Epicardium	RV Endocardium	RV Epicardium
88.83	85.25	79.21	77.89

TABLE II. COMPARISON BETWEEN THE RESULTED SEGMENTATION ERROR AND OTHER RECENT APPROACHES.

	Phase	LV endo	LV epi	RV endo	RV epi
Proposed method	ED	1.8 ± 0.68	1.61 ± 0.65	2.10 ±0. 8	2.27 ± 1.12
	ES	1.84 ± 0.9	1.98 ± 1.12	2.47 ± 1.1	2.1 ± 0.9
Constantinides et al. (2009) [28]	ED,ES	2.35 ± 0.57	2.04 ± 0.47	NR(Not Reported)	NR
Ordas et al. (2003)[29]	5 ph.	1.80 ± 1.74	1.52 ± 2.01d	1.20 ± 1.47	NR
Marak et al. (2009) [30]	ED,ES	2.6 ± 0.38	3 ± 0.59	NR	NR

Mean and standard deviation of the resulted Dice values from segmentation of the endocardial and epicardial borders of the right and left ventricles are reported in Table I.Furthermore, accuracy of the proposed method is validated by clinical indices including end-diastolic volume (EDV), ejection fraction (EF) and left ventricle myocardium mass (MM) are computed. Table II includes the error between the estimated indices from the proposed method and the ground truth from the manual segmentation. The results arecompared with three other approaches in two phases(ED and ES) for the endocardium and epicardium of the left and the right ventricles. The average and maximum of the error is reported as well as the mean, the maximum standard deviation of the absolute error. It can be seen in table I and table II that the results are promising and there is no bias in the error in the estimated cardiac indices. The qualitative and quantitative experimental results support the propose method for simultaneous segmentation of the left and right ventricles by exploiting prior knowledge from a pre-segmented similar image.

IV. CONCLUSION

This paper we proposed a novel framework for segmentation of Right and Left ventricles by iteratively aligning a pre-segmented image to the input image and its segmentation by guided random walks with the aligned drived. The process of guided random walks segmentation and registration iteratively evolves until eventually the pre-segmented image completely aligns the input image and optimal segmentation is achieved. The proposed method allows exploiting prior knowledge in segmentation without constructing a model of shape or appearance. The proposed method was evaluatedby clinical data and its performance was compared with manual segmentation through technical and clinical measurements. The experimental results were promising that suggests the proposed method for dual cavity segmentation of the left and right ventricles in cardiac MRI with prior knowledge.

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