A Framework for Auto-segmentation of Left Ventricle from Magnetic Resonance Images

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Abstract

A practical framework is proposed for the auto-segmentation of the left ventricle (LV) endo-cardium boundary in cardiac magnetic resonance (CMR) images. The segmentation method is based on the random walk (RW) algorithm, which requires user-selected background and foreground seeds. In this paper, the seeds are initialized automatically. The first image frame of a short-axis slice is first partitioned into different regions using the fuzzy clustering algorithm, and the LV region is identified using a heuristic method. Two circular region of interests (ROIs) are then defined based on the estimated centre of the partitioned LV region, which are used as the RW seeds initialization to segment the LV of the first image frame. The centre pixel of the adjacent image frame is then computed using the segmented LV of the previous frame. The foreground and background circular ROIs can then be defined and used as initialization of the RW algorithm to segment the adjacent image. The effectiveness of the proposed framework is verified by the experimental results on real CMR images.

Keywords: Cardiac Magnetic Resonance, Image Segmentation, Random Walk, Left Ventricle, Fuzzy Clustering.

1. Introduction

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. However, manual delineation is tedious, time-consuming, and is limited by inter- and intra- observer variability. In addition, many segmentation algorithms are sensitive to the initialization and therefore the results are not always reproducible, which is also limited by inter algorithm variability. Furthermore, the amount and quality of imaging data that needs to be routinely acquired in one or more subjects has increased significantly. Therefore, it is crucial to develop automated, precise, and reproducible segmentation methods.

Cardiac Magnetic Resonance (CMR) is a well established and rapidly advancing imaging modality in analyzing heart disease. It is considered by some authors to be the reference standard. CMR has proved to be more accurate than echo-cardiology in the calculation of the ejection fraction and also shown superior results in endo-cardium border segmentation. It has a wide topographical field of view and high contrast between soft tissues without the need for a contrast agent. This means there is a high discrimination between the flowing blood and the myocardium muscle. It is non-invasive with high spatial resolution and can be gated using an elec-trocardiogram (ECG) at different phases during the hearts pulse. In this study, the proposed framework aims to segment the left ventricle (LV) endo-cardium border in CMR images.

Segmentation and tracking of LV in CMR data has been extensively addressed for the last decades (Petitjean, 2011; Kang, 2012). Basically, the LV segmentation task can be approached by four major approaches: image-based methods (e.g., Weng, 1997), deformable model-based (e.g., Jolly,

2006) methods, registration-based methods (e.g., Lorenzo-Valdés, 2004), and graph-based methods (e.g., Kedenburg, 2006): The first approach utilizes the basic image analysis operators like thresholding, region-growing, image morphology, edge detection, pixel classification, etc, to delineate the LV boundaries from the image. The second approach trains a shape/curve model of the LV, and lets the curve model evolve in new subjects until it converges to the LV boundaries. The basic idea of the third approach is to transfer those expert-segmentations in training images (i.e., atlases) onto target image through image registration, and then fuse the transferred segmentations to derive an ultimate segmentation. The last approach has also been employed in LV segmentation without heavy reliance on explicitly learned or encoded priors, but the user has to initialize the set of foreground and background seeds.

Graph-based methods have been successfully employed in image segmentation without heavy reliance on explicitly learned or encoded priors. However, graph cuts algorithm proposed in (Boykov, 2000) is a fundamentally two-label algorithm, and susceptible to the "small cuts" problem in the presence of weak boundaries. The random walk (RW) algorithm proposed in (Grady, 2004 & 2006) does not suffer from the "small cut" problem and extends naturally to an arbitrary number of labels. As the good performance of weak boundary detection, noise robustness, and the assignment of ambiguous regions, RW segmentation has been applied in cardiac data, MR brain images (Grady, 2004 & 2006, Eslami, 2013, Dakua, 2011). However, manual selection of the seeds is a hard task in slow intensity varying medical images, and limits its application for real problems.

In this study, a new framework is proposed for the auto-segmentation of the LV endo-cardium boundary in CMR images. The segmentation method is based on the RW algorithm, and the seeds are initialized automatically. The first image frame of a short-axis slice is first partitioned into different regions using the fuzzy c-means (FCM) algorithm (Bezdek, 1981), and the LV region is identified using a heuristic method. Two circular region of interests (ROIs) are then defined based on the estimated centre of the partitioned LV region, which are used as the RW seeds initialization to segment the LV of the first image frame. The centre pixel of the adjacent image frame is then computed using the segmented LV of the previous frame. The foreground and background circular ROIs can then be defined and used as initialization of the RW algorithm to segment the adjacent image. The effectiveness of the proposed framework is verified by the experimental results on real CMR images from RV challenge website (*http://www.litislab.eu/rvsc*).

The rest of this paper is organized as follows: Section 2 reviews the related techniques and presents the proposed framework. The experimental results of the proposed framework are reported in Section 3. Finally, the conclusion is given in Section 4.

2. Methodology

In this section, we first brief review the FCM and RW algorithms, then present the proposed cardiac image segmentation framework, which is specifically for LV endo-cardium boundary delineation in CMR images.

2.1 Fuzzy C-Means (FCM)

Mathematically, FCM algorithm is formulated to minimize the following objective function with respect to the membership function $u_{k|ij}$ and the cluster centre v_k as given by

$$J_{fcm} = \sum_{x_{ij}\in I}\sum_{k=1}^{c}(u_{k|ij})^m \cdot (x_{ij} - v_k)^2 \quad \text{subject to} \quad \sum_{k=1}^{c} u_{k|ij} = 1, \forall x_{ij} \in I \tag{1}$$

Where c is the cluster number, m is the weighing exponent on fuzzy memberships, and a value of m = 2 is known to give good results with the FCM algorithm. Note if m = 1, then the FCM becomes the hard K-means algorithm (Macqueen, 1967) with each point uniquely belonging to its nearest cluster. The $u_{k|ij}$ is the membership of the point x_{ij} in the *kth* cluster. The minimization of (1) gives the updating equations for membership $u_{k|ij}$ and cluster centre v_k, which are given by

$$u_{k|ij} = \frac{(x_{ij} - v_k)^{-2/(m-1)}}{\sum_{k=1}^{K}(x_{ij} - v_k)^{-2/(m-1)}} \qquad \text{and} \qquad v_k = \frac{\sum_{x_{ij}\in I} u_{k|ij}^m x_{ij}}{\sum_{x_{ij}\in I} u_{k|ij}^m} \tag{2}$$

The FCM algorithm is summarized as follows,
1) Fix the cluster number c, initialize the cluster centres $v_{k\ (k=1,2,\ldots c)}$, and set the threshold ε be a small positive value, e.g., $\varepsilon=0.001$.
2) Alternatively update the membership function and cluster centre by using (2) until the changes between two iterations smaller than the threshold ε

2.2 Random Walk (RW)

RW algorithm was first proposed by Leo Grady (2004 & 2006) for performing multi-label, interactive image segmentation. User predefines a series of pixels as the labels, then the probability that a random walker starting at each unlabeled pixel (a pixel can be considered as a node) will first reach one of the prelabeled pixels on different labels is calculated. A high-quality segmentation image can be obtained by assigning to each node the label corresponding to the greatest probability.

The summary of the RW algorithm is described as follows:
1) Obtain a set of marked (or labeled) pixels with K labels (wher 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

$$w_{ij} = \exp(-\beta(g_i - g_j)^2) \tag{3}$$

Where g_i indicates the image intensity at pixel i, and β is the weighting parameter.
4) Solve each label by

$$L_U x^s = -B^T m^s \tag{4}$$

Where x_s ($0 < s \le K$) represents a vector of probabilities for each node to reach to the seeds with label s . Please refer to (Grady, 2006) 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.

The detailed discussion of RW algorithm for image segmentation can be found in (Grady, 2004 & 2006). It is noted that the seeds selection is the key step for RW implementation. Segmentation result is extremely sensitive to the position of seeds, and any improper position of seeds will lead to the false results.

2.3 The proposed framework

This study aims to propose a fully automated framework for cardiac image segmentation with the auto initialization of the background and foreground seeds for RW algorithm. The FCM algorithm and heuristic method are used to locate the LV region in the first image frame of a short-axis slice, then the seeds are initialized based on the centre of the located LV region, after that, the RW algorithm is used to segment the first frame. In sequence, the centre of the segmented LV region of the current frame is then propagated to the adjacent frame to initialize the seeds and RW is used to segment the LV boundary in the frame.

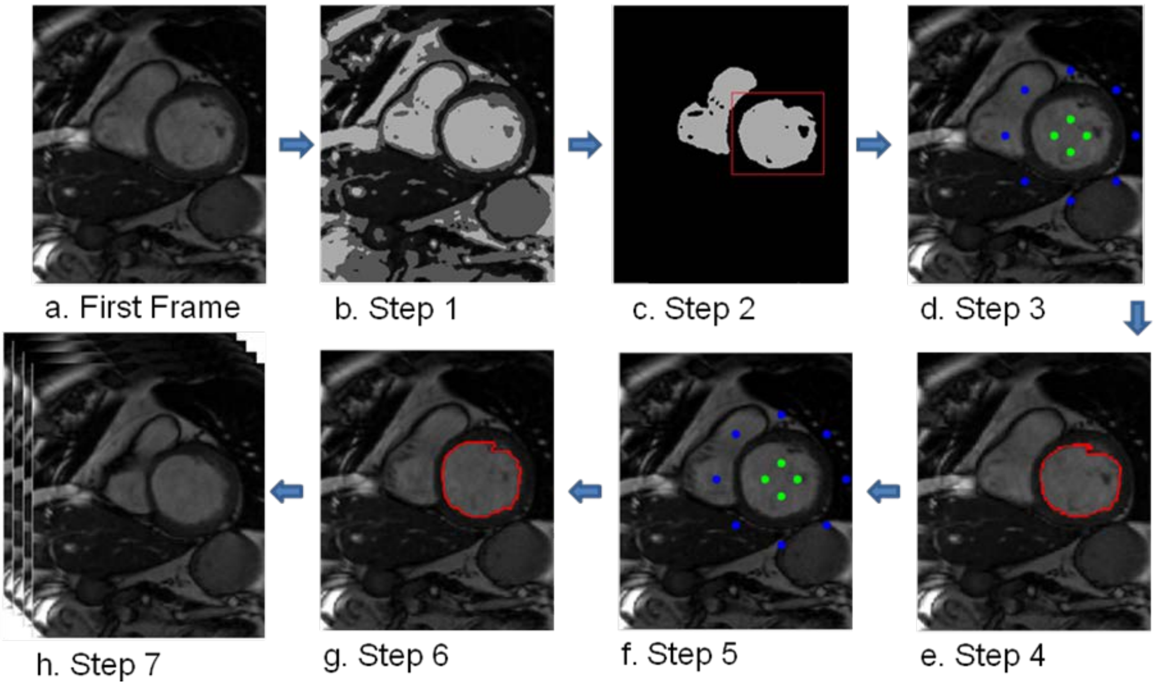

Fig.1 Illustration of the proposed framework for segmentation of a sequence of CMR images, refer to the main text for the details.

The proposed framework for the LV segmentation on a sequence of frames can be summarized as follows,

1) Given the first frame in Fig.1-a, set cluster number c=3, using the FCM algorithm to partition the first frame into different regions with three intensity levels, low, middle and high, as shown in Fig.1-b.

2) Among the regions with high intensity level, choose two big regions whose centres have similar y coordinate, and identify LV as the right one (the left one is right ventricle (RV)), as shown in Fig.1-c. The LV region is indicated by red-colour rectangle.

3) Calculate the centre of LV region, and initialize foreground and background seeds for the first frame, as shown in Fig.1-d. The green-colour and blue-colour dots indicate the foreground and background seeds, respectively.

4) Segment the first frame by using RW algorithm with the initialized seeds from step 3, the segmented LV boundary is shown in Fig.1-e. The Segmented LV boundary is indicated by red-colour curve.

5) Calculate the centre of LV boundary, propagate it to the adjacent frame, and initialize foreground and background seeds for the adjacent frame, as shown in Fig.1-f. The green-colour and blue-colour dots indicate the foreground and background seeds, respectively.

6) Segment the adjacent frame by using RW algorithm with the initialized seeds from step 5, the segmented LV boundary is shown in Fig.1-g. The Segmented LV boundary is indicated by red-colour curve.
7) Repeat steps 5 and 6 to segment the next adjacent frame until it is done on all the frames in the sequence, as shown in Fig.1-h.

The location of LV region in the first frame in step 2 is based on the LV and RV intensity distributions and their overall relevant locations in the CMR images.

3. Experimentation

To evaluate the performance of the proposed framework on cardiac LV segmentation, we apply it to the real CMR images from RV challenge website (*http://www.litislab.eu/rvsc*). In all examples, we fix the cluster number $c=3$ for FCM clustering algorithm and the weighting parameter $\beta=90$ for RW segmentation algorithm. The software used in this study is modified based on the MATLAB source code from L. Grady's homepage (*www.cns.bu.edu/~lgrady*). In all examples, the green dots indicate the foreground seeds, blue dots indicate the background seeds, and red curves indicate the segmented LV boundaries.

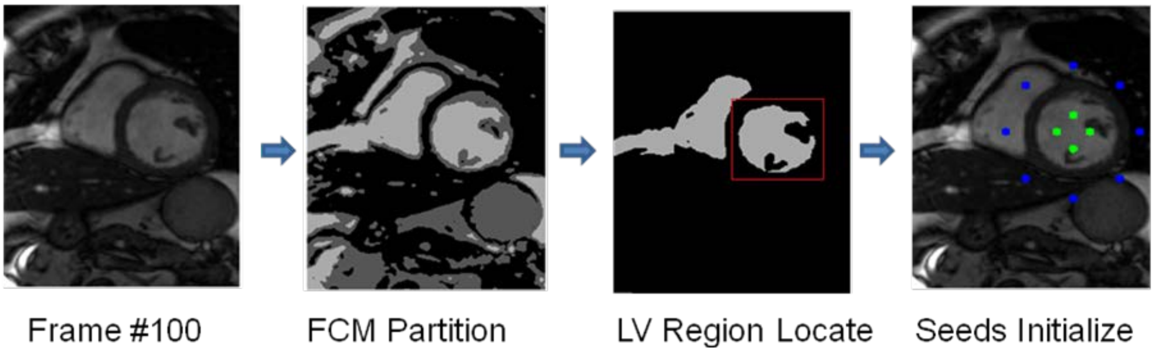

Fig.2 The seeds initialization for the first frame, i.e., frame #100.

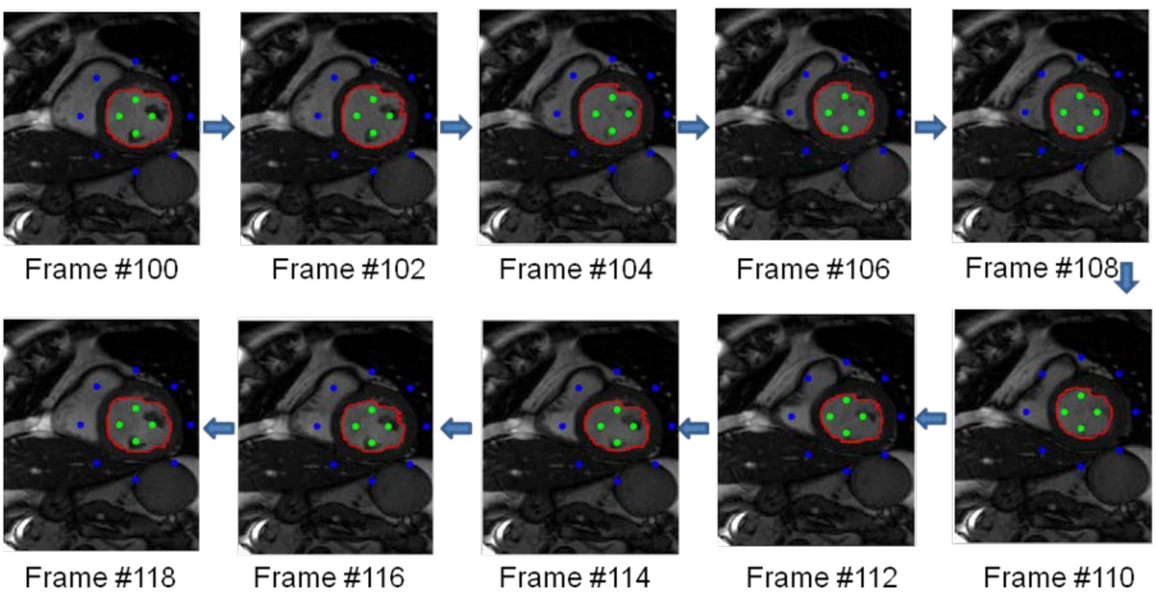

Fig.3 The segmentation results of the proposed framework on the frames #100 to #109 (only show the frames with even number). Here the number of background seeds and foreground seeds are 8 and 4, respectively.

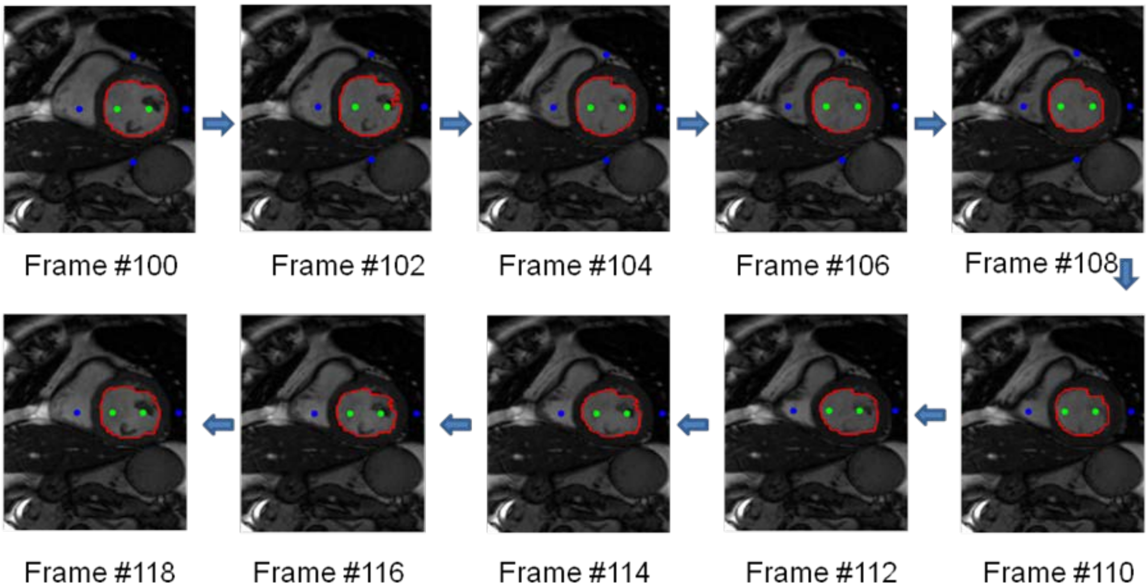

Fig.4 The segmentation results of the proposed framework on the frames #100 to #109 (only show the frames with even number). First row, the number of background seeds and foreground seeds are reduced to 4 and 2, respectively. Second row, the number of background seeds and foreground seeds are reduced to 2 and 2, respectively.

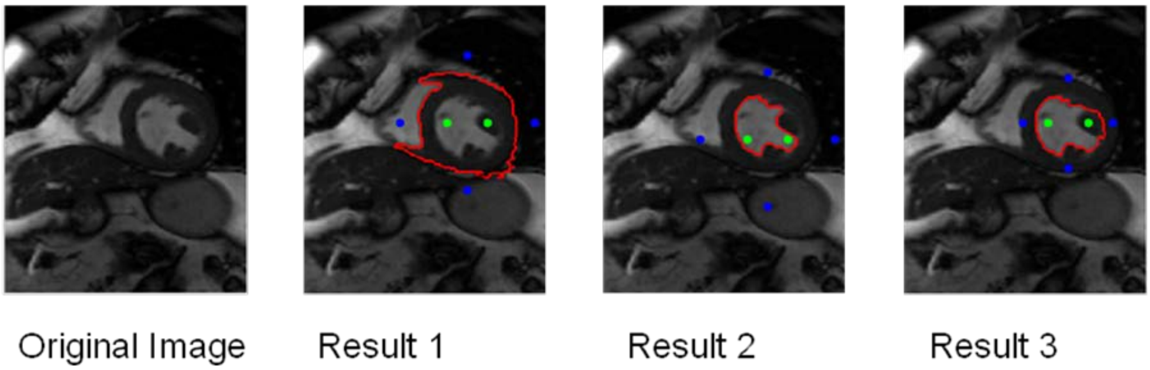

Fig.5 The segmentation results of different seed locations on the same original image. Note the locations of the background and foreground seeds are changed, which affect the segmentation results.

The image size is 256x216, 20 images per cardiac cycle. The testing is performed on the patient #1, frame #100 to frame #119 (one cardiac cycle). We select frame #100 as the first frame, and locate the LV region by using FCM and heuristic method, as shown in Fig.2. The segmented result of the first frame is then propagated to initialize the seeds and segment all the frames in the sequence, as shown in Fig.3. It can be observed from the figure that the segmented LV boundaries are quite reasonable even though papillary muscles are adjacent to or fall inside the LV region in some frames. We need to highlight that whole segmentation procedure is fully automatic processed, which is desirable for practical clinic applications. It is noted that the segmentation results are not sensitive to the number of the seeds, if we reduce the number of background and foreground seeds from 8 and 4 to 4 and 2, or even 2 and 2, respectively, the segmentation results are quite similar, as shown in Fig.4. However, the locations of the background and foreground seeds may affect the segmentation results, as shown in Fig.5, the segmentation may fail if the seeds are not properly located.

4. Conclusion

Accurate and robust extraction of the LV cavity is the key step for analyzing heart functions quantitatively. In this study, we propose a framework for fully automated segmentation of the LV boundary in CMR images in terms of fuzzy clustering and graph segmentation techniques. The effectiveness of the proposed framework has been verified by the experimental results of LV segmentation on real CMR images. This study focuses on LV endocardial delineation only, to extend the proposed framework for LV epicardial delineation is one of the future research topics.

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