

Belongingness Clustering and Region Labeling Based Pixel Classification for Automatic Left Ventricle Segmentation in Cardiac MRI Images

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Abstract

This paper presents a fully automatic rapid method for delineation of the left ventricle (LV) from MRI images of heart patients for the critical diagnosis of myocardial function as an evaluation of heart disease. In this research, completely automated image segmentation is performed using a belongingness clustering and region labeling based pixel classification approach. This new combined region labeling and belongingness clustering technique removes the need for manual initialization, which is required in deformable methods. The left ventricle is segmented automatically in all slices in the multi-frame MRI data of the whole cardiac cycle rapidly in 0.67 seconds for a single frame on average. Manual segmentation of the left ventricle in the multi-frame cardiac MRI image data by experts was used as a standard to test the accuracy of the automated left ventricle segmentation method. Medical parameters like End Systolic Volume (ESV), End Diastolic Volume (EDV) and Ejection Fraction (EF) were calculated both automatically and manually and compared for accuracy.

Introduction

Magnetic resonance is a well-established modality in cardiac imaging used for measuring the cardiac function of a patient's heart. Computed tomography (CT), single-photon emission computer tomography (SPECT), positron emission tomography (PET), and ultra-sound (US) are other common imaging modalities used by radiologists to examine cardiac dysfunction. The advantage of MRI, along with being non-intrusive and radiation-free, is that the scan is of good quality resolution as compared to the other methods, which is important for accurate segmentation of the left ventricle for diagnosing disease in a patient's heart.

A number of methods are conventionally used for left ventricle segmentation in MRI images of the heart. Primarily, they can be categorized as edge detection, region based segmentation, and pixel classification. The edge detection method is based on tracing edges or ridges in the images [1] and the region-based method is based on pixel similarity of image regions [2]. Edge-based or line-detection technique delineates the edge of the left ventricle. The delineated or traced ridge or line segments the region of interest

from its background and other noise elements. Region-based segmentation starts with a region initialized at a seed point that grows to include neighborhood pixels until the pixel similarity or pixel intensity changes drastically beyond a certain threshold [3]. The pixel classification method divides pixels into groups based on pixel similarity measures such as their intensity, texture, color, gray level, etc. K-means, fuzzy c-means clustering, and graph cut methods are different types of pixel classification methods [4]. Belongingness based clustering employed in this research relies on pixel intensity and location for dividing an image into two or more clusters [5-7].

In this paper, belongingness based clustering and region labeling pixel classification is used to segment the region of interest, i.e. the left ventricle. This method labels neighboring pixels that are connected after belongingness based clustering classifies pixels as foreground or background. Pixels in a group will be labeled with the same level and thus segregated into different regions. The region that corresponds to the left ventricle is chosen based on the heuristics of pixel location (since the left ventricle will be in the center of the cardiac image) and region boundary eccentricity

(since the left ventricle is circular). Hence, in this research, an innovative belongingness clustering cum region labeling pixel classification method is used to achieve sub-second fast fully automatic segmentation of the left ventricle in all frames in the complete cardiac cycle without any seed point initialization or user intervention.

Methodology

As **Figure 1** illustrates, the left ventricle in the multi-frame MRI images was segmented using a series of algorithms:

Automatic Segmentation Algorithm

Belongingness clustering was used to group the MRI image pixels into two clusters – foreground and background with image-based thresholding of the MRI input image frame. After belongingness clustering, region labeling pixel classification is performed to remove other non-ventricle regions from the segmented foreground. Thus region labeling pixel classification differentiates the left ventricle from other foreground clusters such as the right ventricle and other parts of the heart. Median filtering removes the noisy regions from the foreground clusters.

Region labeling pixel classification uses the heuristics–distance from the image center and eccentricity to select which connected cluster is the left ventricle. In other words, the left ventricle region is the one with the highest circularity (lowest eccentricity) closest to the image center point (smallest distance from the image center point). The left ventricle region boundary is delineated as the pixels traced at the boundary of the left ventricle region.

Belongingness Clustering

Belongingness clustering groups similar pixels into clusters such that similar pixels are grouped into the same cluster, and dissimilar pixels are in different clusters. Pixel intensity, connectivity, and distance are the similarity measures used to group the pixels.

Contrary to hard clustering, where a pixel can only belong to a single cluster, belongingness clustering is soft clustering, in which pixels can be members of multiple clusters. The belongingness to a certain cluster is higher if the level of belongingness to that cluster is higher.

Belongingness clustering divides n pixels into a group of c belongingness clusters based on pixel similarity. A number of c cluster centers are defined where a partition matrix contains elements defining belongingness levels w_{ij} , i.e. measures of belongingness of pixel x_i to cluster c_j . In this belongingness clustering method, the objective function given in equation (1) below is minimized.

$$w_k(x) = \frac{1}{\sum_j \left(\frac{d(\text{center}_{k,x})}{d(\text{center}_{j,x})} \right)^{2/(m-1)}} \quad (1)$$

The belongingness levels or membership to clusters for each pixel is iteratively updated with minimization of the objective function in equation (1). When the difference in belongingness levels over a single iteration is less than a certain threshold, the iteration is ended, at which point each pixel is assigned to belong to whichever cluster it has the greatest belongingness or membership level for.

This function contains belongingness values u_{ij} and the fuzzifier m , which defines cluster fuzziness. Higher cluster fuzziness means lower belongingness levels. If $m = 1$, the belongingness w_{ij} become 0 or 1, which means discrete partitioning.

Each pixel x has a group of belongingness or membership level coefficients $w_k(x)$ that decide the pixel's belongingness to the k th cluster. The cluster center is calculated as the average of all pixels weighted by their cluster belongingness level:

$$C_k = \frac{\sum_x w_k(x)^m x}{\sum_x w_k(x)^m} \quad (2)$$

The level of belongingness or membership, $w_k(x)$, is proportional inversely to the distance between the cluster center (from the past iteration) and pixel x . The fuzzifier parameter m controls how much weight is assigned to the closest cluster center. The following steps are used for execution of the belongingness clustering algorithm in our work:

1. Choose the number of clusters.
2. Determine the belongingness cluster centers.
3. Iteratively update the partition matrix until the change in belongingness levels is less than a given threshold.
4. Assign each pixel to the cluster for which it has the highest belongingness or membership.

Results

Figure 2 illustrates the automatic segmentation of the left ventricle in one of the multiple MRI frames using belongingness clustering and region labeling pixel classification. This procedure is fast because it does not require any iterations or initialization from user intervention and can thus be repeated on several MRI image frames for fast fully automatic multi-frame segmentation. **Figure 3** shows that our method fully automatically reads in and segments the LV in all frames in the complete cardiac cycle



Figure 1 Flow-chart of fast fully automated segmentation of cardiac MRI for left ventricle extraction.

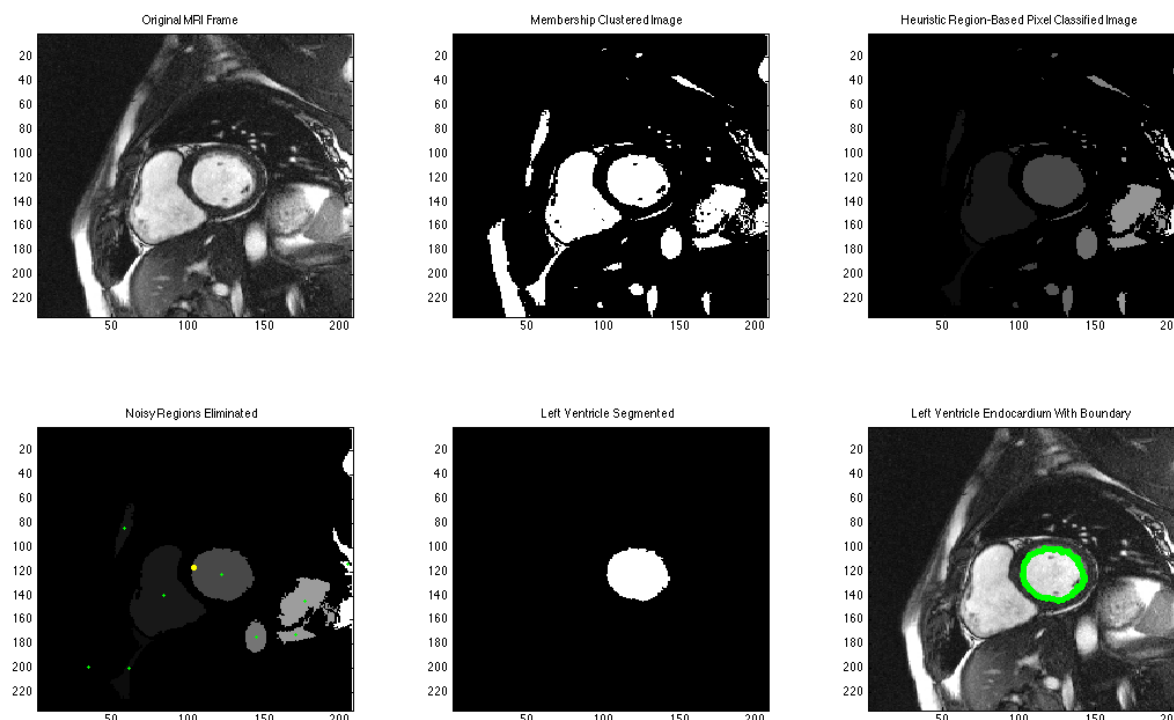


Figure 2 Fully automatic segmentation of the left ventricle using belongingness clustering and region labeling pixel classification.

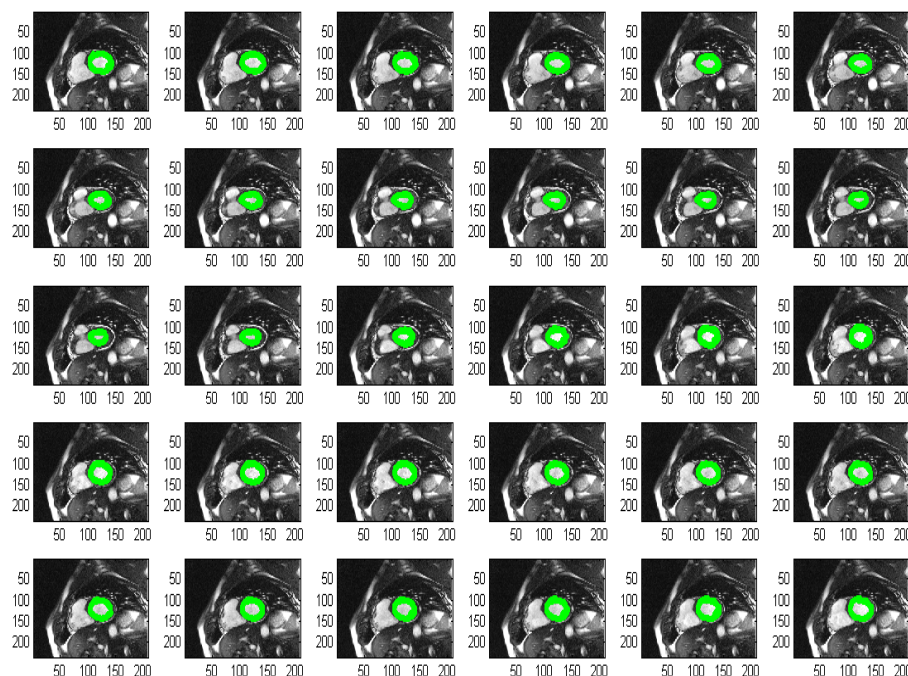


Figure 3 Fully automatic segmentation of the left ventricle in all frames of the full cardiac cycle in multi-frame cardiac MRI.

in multi-frame cardiac MRI. **Figure 4** plots the left ventricle volume calculated from the area, i.e., the number of pixels in the segmented LV region versus the MRI image frame number. The volume of the left ventricle is calculated as: Volume (mm³)=Area (number of pixels) * Pixel Dimensions (in mm²) * Slice Thickness

(in mm). In the graph, the systolic and diastolic phases are evident, which is another validation of the completely automated left ventricle extraction and area and volume measurement in all slices across the complete cardiac cycle in the multi-frame MRI.

Table 1 shows the comparison of medical parameters like End

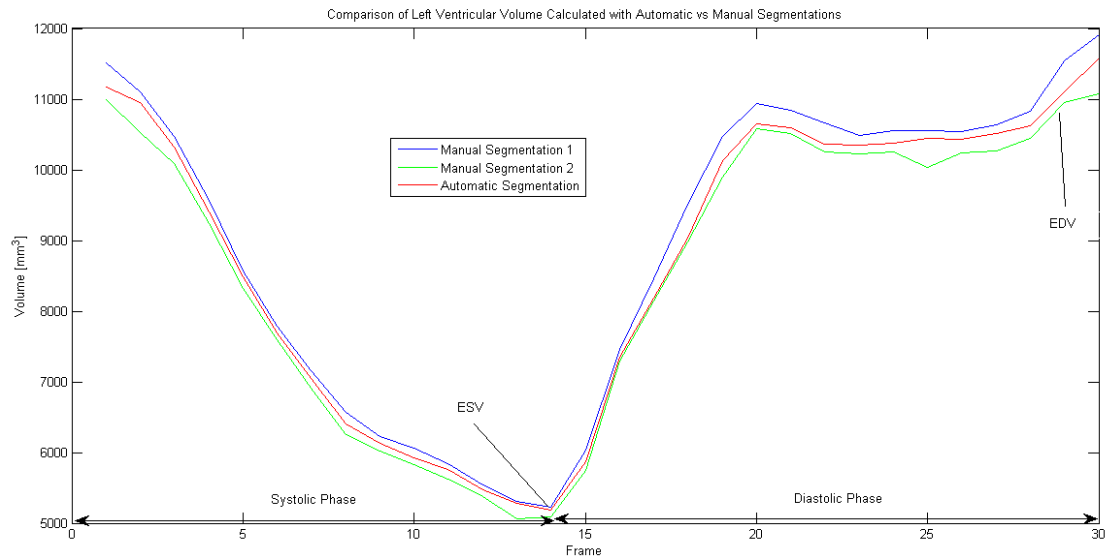


Figure 4 Left ventricle volume plotted over the full cardiac cycle

Systolic Volume (ESV), End Diastolic Volume (EDV), Stroke Volume (SV) and Ejection Fraction (EF) calculated from the automatic and manual segmentations using the formulas given in the equations below:

$$\text{Stroke Volume (SV)} = \text{EDV} - \text{ESV}$$

$$\text{Ejection Fraction (\%)} = (\text{SV}/\text{EDV}) \times 100$$

The accuracy of the automatic method is sufficiently validated given manual tracing as the gold standard since the correlation between automatic and manual tracing is higher than two manual tracings (see **Figure 5**). The correlation coefficient between the automatic and manually traced LV boundaries (0.945 on average)

was greater than the correlation coefficient between two different sets of manually traced LV boundaries (0.855 on average).

Discussion

Our new clustering cum labeling technique in this paper is fully automatic and free of user intervention or seed point initialization. Belongingness clustering and region labeling pixel classification rapidly segments the left ventricle in 0.67 seconds on average for a single frame, i.e. 22 seconds for all frames of the full cardiac cycle. Hence this method's left ventricle segmentation computational time is much less than deformable active snake models or level sets methods, which require several iterations.

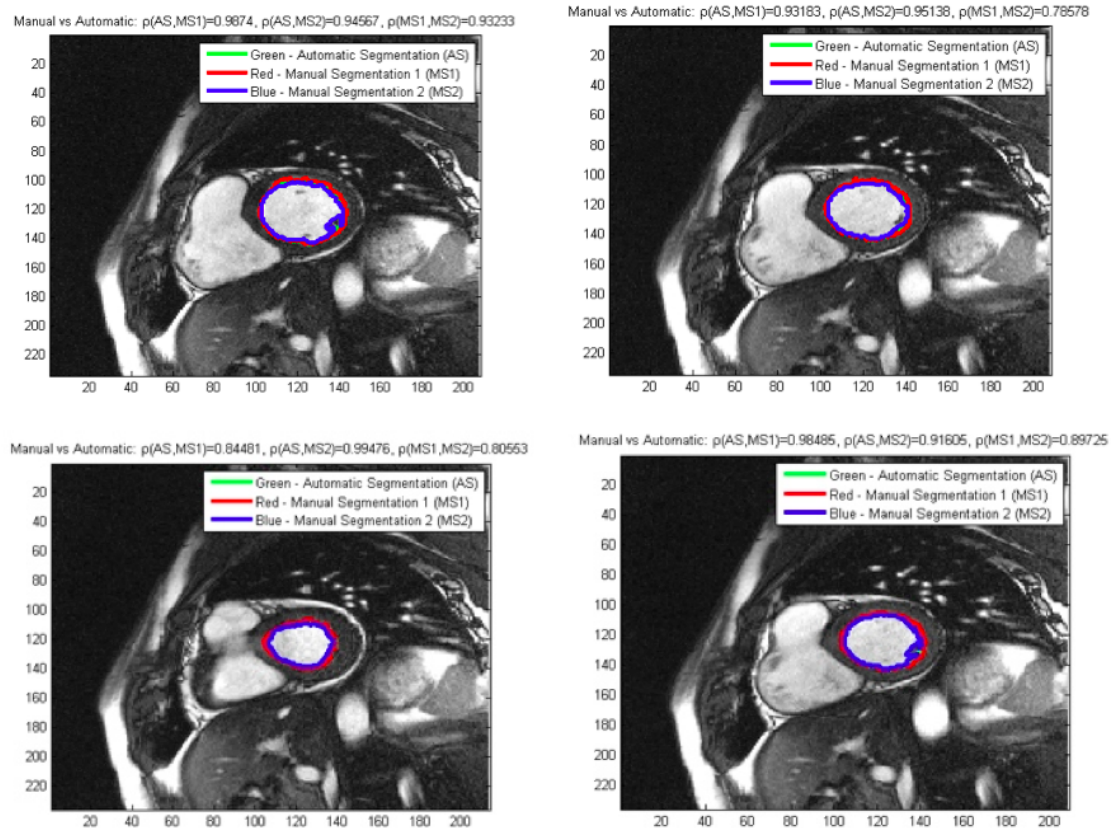


Figure 5 Accuracy of LV segmentation validated with manual tracing.

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