Fully Automated Assessment of Left Ventricular Volumes, Function and Mass from Cardiac MRI

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Abstract

The importance of quantification of left ventricular (LV) size, function and mass is increasingly recognized through growing evidence about the prognostic value of these indices and their diagnostic role in patient follow-up during therapy. However, quantitative evaluation from cardiac magnetic resonance (CMR) images relies on manual tracing of LV endo- and epicardial boundaries, which is subjective and time-consuming. Our goal was to develop a fully automated technique for the detection of these boundaries to assess LV volumes, ejection fraction (EF) and mass. Our automated approach consists of: 1) identification of the LV cavity based on detection of moving and circular structures in short-axis views; 2) endocardial detection using a region-based probabilistic level set model to allow volume measurements throughout the cardiac cycle; 3) epicardium detection at end-diastole based on an edge-based level set model to allow LV mass measurement. This approach was tested in 10 patients by comparing automatically derived LV volumes, EF and mass using manual tracing as a reference. Automated detection of the endo- and epicardial boundaries took <5 minutes per patient on a standard PC. The detected boundaries were in good agreement with manual tracing. As a result, LV volumes, EF and mass showed good inter-technique concordance, reflected by minimal biases and narrow limits of agreement. The proposed technique allows fully automated, fast and accurate measurements of LV volumes, EF and mass from CMR images, which may address the growing clinical need for quantitative assessment.

1. Background

Cardiac Magnetic Resonance (CMR) allows high resolution, radiation free, dynamic, multi-plane imaging of the heart. This imaging modality has become the standard reference technique for accurate and reproducible evaluation of left ventricular (LV) size, function and mass [1]. Although semi-automated LV boundary detection is available in most commercial software packages for analysis of CMR images, it is usually based on algorithm parameters that are affected by image quality and depend on the specific pulse sequence [2]. As a result, the computation of LV volumes, ejection fraction (EF) relies on frame-by-frame manual tracing of endo- and epicardial contours on multiple short-axis planes. This methodology is subjective, experience dependent, tedious and time-consuming, due to the large numbers of acquired images that represent the entire cardiac cycle in multiple planes. Consequently, in clinical practice, analysis is usually limited to quantitative measurements of end-diastolic (ED) and end-systolic (ES) frames. This approach does not utilize potentially important temporal information that can be derived from dynamic changes in LV volume, such as LV diastolic function.

The goal of this study was to develop a fully automated technique for the dynamic detection of LV endo- and epicardial boundaries from short-axis CMR images. Our hypothesis was that such a technique would improve the accuracy of CMR quantification of LV size, function and mass and allow fast, objective, more detailed, accurate assessment of LV function.

2. Methods

2.1. CMR imaging

CMR data were obtained in 10 patients using a 1.5T scanner (Intera Achieva, Philips, Best, Netherlands) at the Cardiac Imaging Center of the University of Chicago. Cine-loops were acquired during 10 to 15 second breath-holds in 8 to 14 short-axis slices from the mitral annulus to LV apex using a steady-state free precession dynamic gradient-echo pulse sequence. Imaging parameters included: echo time =1 ms, repetition time =3 ms, flip angle =60°, slice thickness =8 mm with no gaps, scan matrix size =256x256 and pixel spacing =1.40 mm^2. Temporal resolution was 30 frames per cardiac cycle.

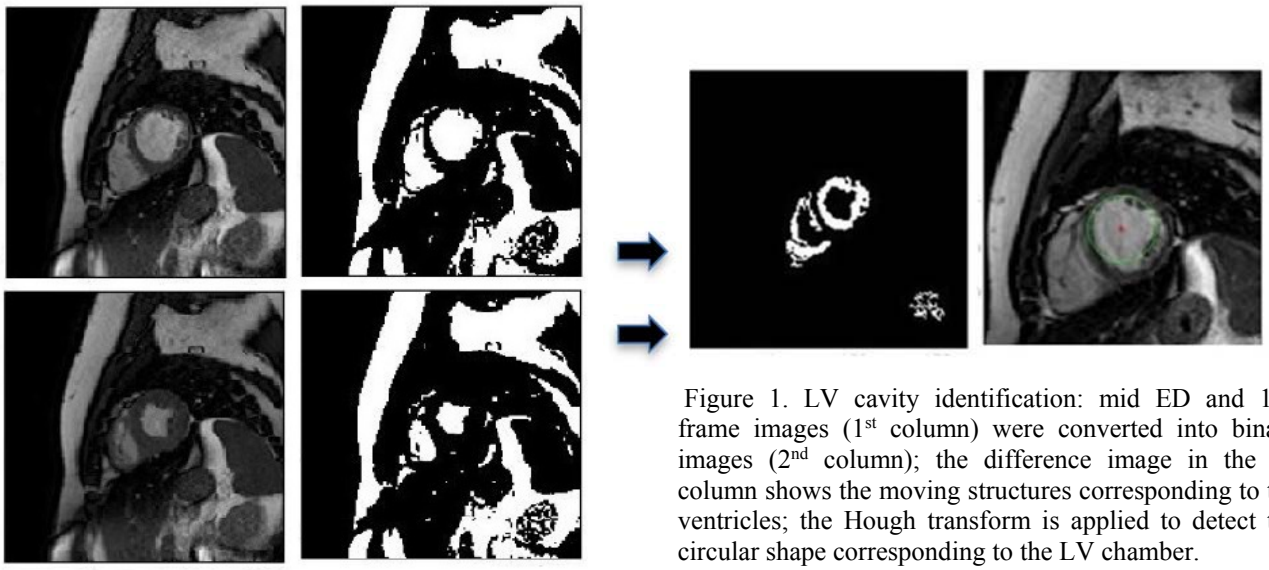

Figure 1. LV cavity identification: mid ED and 15th frame images (1st column) were converted into binary images (2nd column); the difference image in the 3rd column shows the moving structures corresponding to the ventricles; the Hough transform is applied to detect the circular shape corresponding to the LV chamber.

2.2. Image analysis

LV slices were selected for analysis beginning with the highest basal slice where the LV outflow tract was not visible, and ending with the lowest apical slice where the LV cavity was visualized. LV endocardial and epicardial contours were manually traced at ED and ES with the papillary muscles included in the LV cavity, by an experienced investigator. This resulted in LV cross-sectional area for each slice over time. Global LV volumes were computed throughout the cardiac cycle using a disk-area summation method, from which ED and ES volumes (EDV and ESV, respectively) were obtained as the maximum and the minimum volumes and EF was calculated as (EDV-ESV)/EDV•100. LV mass was computed at ED as 1.05•(Vepi-EDV), where Vepi is the volume included in the epicardium.

CMR datasets were analyzed using custom software for automated LV endocardial and epicardial contours detection (Matlab R2013a, The MathWorks Inc.). The main steps of this technique are: 1) fully automated identification of the LV cavity, based on the detection of moving and circular structures in the images [3,4]; 2) endocardium segmentation based on region-based probabilistic level set model [5,6]; 3) epicardium segmentation based on an edge-based level set model [7].

The segmentation process required an initial condition that was automatically defined. LV cavity was identified by assuming the heart is the only moving structure in the CMR images; therefore we looked for differences in ventricular morphology in a mid-ventricular slice between ED and a frame in the middle of the cardiac cycle (fig. 1). Digital subtraction of binarized images of these two frames resulted in a rough detection of the position of the left and right ventricles. Considering that LV shape is almost circular on short-axis images, the application of the Hough Transform for circular shape detection [3,4] allowed us to identify the LV cavity. The same process was then repeated for all slices from base to apex. Images were then cropped around the detected areas to increase segmentation method robustness and reduce computational processing time. The center of the circle was used to define the initial condition for the segmentation step in each plane.

Endocardial boundaries were automatically detected by applying a region-based level set segmentation procedure, based on statistical model using information related to image noise distribution [5,6]. This method drives level set curve evolution to slice partitioning into maximally homogeneous regions, taking into account CMR noise distribution. Since the presence of papillary muscles and trabeculae did not allow adequate delineation of the endocardial borders, the endocardial contour was corrected by applying an additional evolution only in a mask region, defined to automatically include papillary muscles and trabeculae inside the LV cavity. The mask was created considering the difference between the previously detected curve and a curve obtained by processing a filtered version of the original image applying the Perona-Malik anisotropic filter [7] to homogenize gray levels intensity inside the LV chamber.

Epicardial boundaries were obtained by applying an edge-based level set model, based on curvature, ballooning and advection terms [8] and using the previously obtained mask as a weight matrix for the edge indicator. Initial condition for epicardial segmentation was set using the previously computed endocardium contour.

Initially, wall thickness was roughly estimated by considering gray level histogram along a specific direction [9] and the endocardial curve was expanded considering this measurement (fig. 2). Epicardial contour refinement was achieved by applying the Malladi-Sethian model, to take into account variations in myocardial thickness.

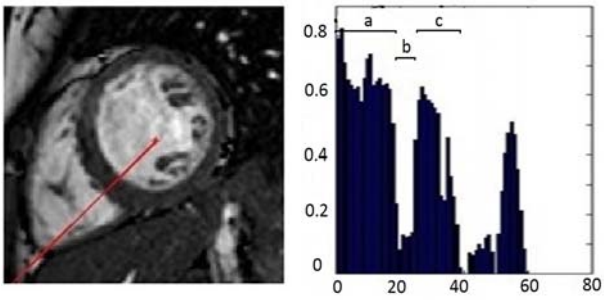

Figure 2. Evaluation of myocardial thickness: wall thickness was roughly computed in each slice starting from the radius marked from the previous endocardial initial point towards the right ventricle. The histogram along this direction allowed the detection of the LV cavity (a), RV cavity (c) and the myocardial tissue (b).

This segmentation procedure was applied to the ED frame in each slice. To extend the contour delineation throughout the cardiac cycle, we hypothesized the LV does not significantly move between subsequent frames. This assumption allowed to set, as initial condition for the following frames, the detected contours at previous frame. Contour refinement was obtained by applying the Malladi-Sethian model to detect the LV endo- and epicardial boundaries in the following frames.

2.3. Statistical Analysis and similarity indices

Statistical analysis was performed using Matlab software. Comparisons between automated and manual measurement of EDV, ESV, EF and mass included linear regression and Bland-Altman analyses. For each parameter, significance of the differences between the two techniques was tested using two-tailed, paired student's t-tests. To evaluate the similarity between the automatically and manually traced boundaries, Hausdorff distance and similarity indices were computed, including Dice coefficient and Jaccard index. In addition, inter-technique discordance in border position was estimated as the point-by-point sum of absolute differences between the radial distances from the LV cavity area center normalized by the average contour radius.

3. Results

For each patient, time required for automated segmentation for all slices throughout the cardiac cycle was approximately 6 minutes on a standard PC (Intel Core i5-2410M CPU @ 2.30 GHz, RAM 4 GB). A total of 110 slices were analyzed. LV cavity was successfully identified in 107/110 images (fig. 3). LV chamber was not correctly identified in at ES in 3 apical slices, due to partial volume artifacts resulting in poorly defined endocardium.

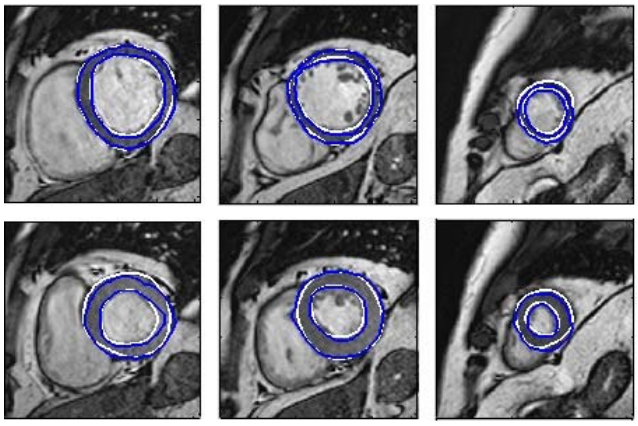

Figure 3. Example of endo- and epicardial contours in the ED (top) and ES (bottom) frames for LV basal, mid-ventricular and apical slice (from left to right), obtained by applying the automated technique (blue) and manual tracing (white).

Linear regression analysis between the automated technique and the manual reference showed very good correlations and regression slopes for EDV, ESV, EF and mass (fig. 4). Bland-Altman analysis (Table 1) showed no significant biases between the automated technique and the reference technique for ESV and EF, while EDV and mass showed small but significant overestimation ($p<0.05$). Importantly, the bias expressed as % of the manual reference values was <8% for all the parameters. The 95% limits of agreement were relatively narrow (Table 1), providing additional support to the good agreement between the two techniques.

Table 1. Results of the Bland-Altman analysis.

Parameters	Bias	Bias (% of the measured value)	95% limits of agreement
EDV	-8±7 ml	4.1 %	-22÷7 ml
ESV	-3±9 ml	3.4 %	-23÷17 ml
EF	0.2±5 %	0.35 %	-10÷11 %
Mass	-8±7 g	7.4 %	-24÷7.1 g

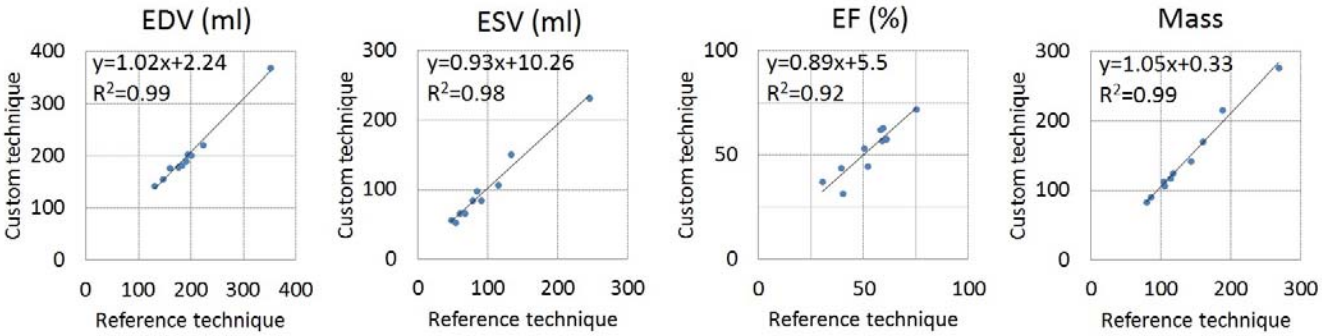

Figure 4. Linear regression analyses of LV EDV, ESV, EF and mass obtained by the automated technique compared to the manual reference.

Similarity metric results between manually traced and automatically obtained contours are shown in Table 2. Inter-technique discordance in boundary position was more pronounced near the apex (Fig. 5), which is not surprising in view of the known relatively poor endo- and epicardial definition in short-axis slices, as a result of partial volume artifacts that are more pronounced at this level of the ventricle.

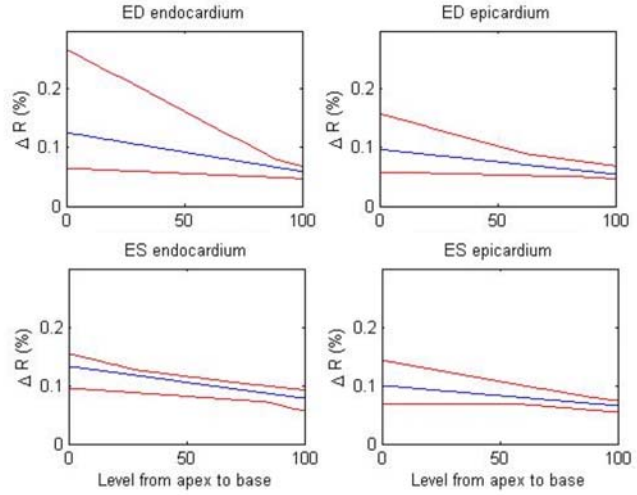

Figure 5. Distance between the automated and manually traced endo- (left) and epicardial (right) boundaries at ED (top) and ES (bottom) at different levels of the left ventricle (every 1% of the LV length) averaged in 10 patients (blue lines represent mean values; red lines SD). Data shown in percent of the measured radius (%ΔR).

Table 2. Comparison between the automatically detected and manually traced endo- and epicardial contours in all slices for the ED and ES frames.

Indices	ED		ES	
	Endo	Epi	Endo	Epi
Dice	0.93±0.06	0.95±0.03	0.91±0.04	0.89±0.11
Jaccard	0.88±0.09	0.90±0.06	0.83±0.07	0.82±0.16
Hd(pixel)	3.4±0.46	3.7±0.51	3.4±0.51	3.8±0.55
Hd(mm)	1.7±0.32	1.9±0.39	1.7±0.35	1.9±0.42

4. Conclusions

The proposed technique for automated detection of endo- and epicardial LV boundaries overcomes the limitations of the conventional technique based on manual tracing and provides very similar measurements of LV size, function and mass. The results of this pilot study demonstrated the feasibility of this technique and its accuracy in a small number of patients, as reflected by minimal biases and similarity indices.

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