Improved Automated Quantification of Left Ventricular Size and Function from Cardiac Magnetic Resonance Images

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Abstract

Assessment of left ventricular (LV) size and function from cardiac magnetic resonance (CMR) images requires manual tracing of LV borders on multiple 2D slices, which is subjective, experience dependent, tedious and time-consuming. We tested a new method for automated dynamic segmentation of CMR images based on a modified region-based model, in which a level set function minimizes a functional containing information regarding the probability density distribution of the gray levels. Images (GE 1.5T FIESTA) obtained in 9 patients were analyzed to automatically detect LV endocardial boundaries and calculate LV volumes and ejection fraction (EF). These measurements were validated against manual tracing. The automated calculation of LV volumes and EF was completed in each patient in <3 min and resulted in high level of agreement with no significant bias and narrow limits of agreement with the reference technique. The proposed technique allows fast automated detection of endocardial boundaries as a basis for accurate quantification of LV size and function from CMR images.

1. Introduction

It is widely agreed that comprehensive evaluation of cardiac function for the diagnosis and therapeutic follow up of myocardial pathologies requires a wide range of information. Thus, left ventricular (LV) volume over time curves provide clinically important information on LV dynamics, beyond the traditional ejection fraction (EF), which include direct insight into LV contraction and relaxation properties closely related to pathophysiology of various disease states. Cardiac Magnetic Resonance (CMR) provides noninvasive, high-resolution, radiation-free, dynamic imaging of the heart that allows accurate and reproducible evaluation of LV volumes throughout the cardiac cycle. Over the last decade, this methodology has become the standard reference technique for LV volume and EF measurements, against which other techniques are validated [1,2].

Although automated LV endocardial boundary detection is available in commercial software for analysis of CMR images, it is usually based on algorithm parameters that are sensitive to image quality and frequently depend on the specific imaging protocol [3]. Since optimization of these parameters for each individual pulse sequence is not possible, the computation of LV volumes and EF in clinical practice relies on frame-by-frame manual tracing of endocardial contours on multiple short-axis planes. This procedure is subjective, tedious, time-consuming and experience-dependent. Furthermore, its accuracy relies on geometrical models, such as disk-area summation, which may not always yield accurate results.

Accordingly, our aim was to develop and test a technique for fast, automated, dynamic segmentation of CMR images, that would take into account image attributes specific to each pulse sequence.

Our approach uses a region-based level set model described by Chan and Vese in [4]. This segmentation model is based on the minimization of an energy function containing information regarding the grey level values of the pixels into the image. The minimization of this energy function leads to the segmentation of the image in regions for which the difference in the grey level intensity average inside and outside is maximized.

In our model we keep the region-based approach and embed in the segmentation model the a priori knowledge of statistical distribution of grey levels in CMR data: therefore the proposed method drives the curve evolution to achieve a maximum likelihood segmentation of the target with respect to the statistical distribution law of image pixels. We consider the noise in CMR images to have a Rician probability density function that approaches a Gaussian function when pixel intensity is higher than the noise level [5,6]. Our segmentation method was implemented in the 3D domain and requires a simple definition of a reference point of view within the data as initial condition for the dynamic detection of the LV endocardial boundaries throughout the cardiac cycle.

2. Methods

2.1. CMR imaging

CMR data were obtained in 9 patients using a 1.5 Tesla scanner (General Electric) with a phased-array cardiac coil. ECG-gated localizing spin-echo sequences were used to identify the long-axis of the left ventricle. Steady-state free precession dynamic gradient-echo mode (FIESTA) was then used to acquire images during 10 to 15 sec breath-holds. Cine-loops were obtained in 6 to 10 short-axis slices, from the atrio-ventricular ring to the apex (9 mm slice thickness, no gaps) with a temporal resolution of 20 frames per cardiac cycle.

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. In every slice, LV endocardial contours were manually traced frame-by-frame (MASS Analysis, GE) 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 end-diastolic and end-systolic volumes (EDV and ESV, respectively) were obtained as the maximum and minimum volumes and EF was calculated as (EDV-ESV)/EDV •100.

In addition, the CMR datasets were analyzed using custom software for automated LV endocardial contours detection. For each frame, the 2D CMR slices were stacked and 3D segmentation was automatically performed throughout the cardiac cycle to obtain endocardial contours. This was achieved by using a modified region-based model, in which a level set function minimizes a functional $l(I,C)$ containing information regarding the Gaussian probability density distribution of the gray levels $p(I)$:

$$p(I) = \frac{1}{\sqrt{2\pi}\sigma} exp\left(-\frac{1}{2}\left(\frac{I(x,y,z) - \mu)}{\sigma} \right)^2 \right) \qquad (1)$$

where $I(x,y,z)$ is the image intensity in the CMR dataset defined in $\Omega \subset R^3$, μ and σ are the average and standard deviation of $I(x,y,z)$, respectively.

The energy functional $l(I,C)$, in which we included the information regarding the statistical distribution $p(I)$ of grey levels in CMR data was defined as:

$$l(I,C) = \varepsilon \cdot lenght(C) + \int_{\Omega_i(C)} \log p(I)\, dxdydz + \int_{\Omega_o(C)} \log p(I)\, dxdydz \qquad (2)$$

where C is a surface partitioning the dataset in two regions, inside the surface C, $\Omega_i(C)$, and outside C, $\Omega_o(C)$ and $\varepsilon \cdot length(C)$ is a regularization term [7]. This functional reaches its maximum when the curve C has partitioned the dataset $I(x,y,z)$ in maximally homogeneous 3D regions.

To obtain the first variation of $l(I,C)$ we introduced the level set function $\varphi: \Omega \rightarrow R$ and implicitly defined the curve C as the zero level set of φ [8,9]. The initial condition for the evolution of the level set function φ was computed by manually selecting one point inside the LV chamber in one mid slice of the end diastolic dataset. From this reference point, the initial surface was calculated as:

$$\varphi(x,y,z) = \sqrt{(x-x_0)^2 + (y-y_0)^2 + (z-z_{slice})^2} + R$$

where (x_0,y_0) is the reference point chosen by the operator, z_{slice} is the height of the mid slice, and R is a constant term that changes automatically for each frame in the cardiac cycle.

Starting from this initial surface, this function evolves guided by equation (2) for each frame. The evolution process stops when the region probability terms of the inside regions equal the terms of outside regions, up to the regularization of the surface. At the end of the evolution, the undesired detected regions outside and inside the LV chamber, characterized by the same noise distribution, are automatically removed from the zero level set function. This deletion does not require any manual intervention and is fully automated, since the coordinates of the selected point is known.

This procedure results in the detection of LV endocardial boundaries throughout the cardiac cycle. To be consistent with the reference, volumes inside the detected surfaces were computed using the disk-area summation method. From these volume-time curves, EDV and ESV were obtained as the maximum and minimum volumes reached during in the cardiac cycle and EF was calculated.

Matlab 6.1 (The MathWorks Inc.) environment was used for software implementation. To speed up the segmentation procedure, the region-based algorithm was implemented in the C++ language.

2.3. Statistical analysis

Statistical analyses were performed using Matlab software (The MathWorks Inc.). Comparisons between automated and manual measurements of EDV, ESV and EF included linear regression and Bland-Altman analyses. The significance of differences between the two techniques was tested using paired t-test. P-values <0.05 were considered significant. In addition, percent discordance between LV volumes obtained by manual tracing and the automated analysis was calculated for each pair of volume curves as the point-by-point sum of

absolute differences between the corresponding values, normalized by the point-by-point sum of the manually traced volumes.

3. Results

The operator selects one point in the image (fig. 1,A) and the automated analysis of a set of images was completed (fig. 1, B and C) in less than 3 min per patient on a personal computer (AMD Athlon XP 2800). In contrast, manual tracing of the same images using the standard methodology required between 10 and 20 minutes for each patient.

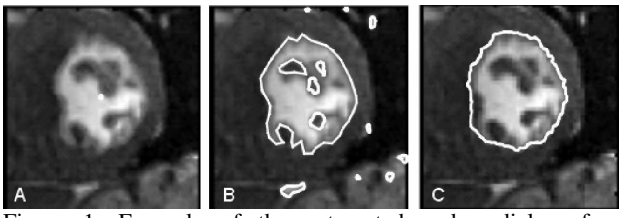

Figure 1. Example of the automated endocardial surface detection in one slice: (A) initial point selection; (B) result of the maximum likelihood segmentation; (C) final endocardial contour after the automatic deletion of the undesired detected regions outside and inside the LV chamber.

Figure 2 shows an example of the LV endocardial contours detected at one phase of the cardiac cycle at different levels from LV base to apex. Importantly, papillary muscles and trabeculae were automatically included in the blood pool. Volume-time curves obtained in one patient by manual tracing and by the automated technique are shown in Figure 3.

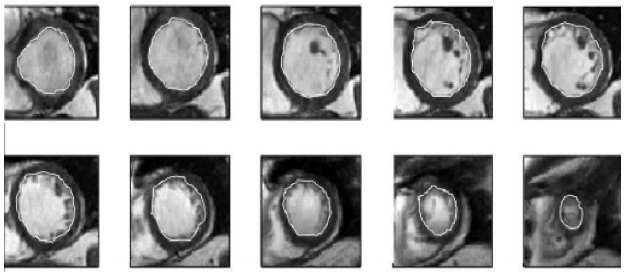

Figure 2. Example of the detected endocardial contours in one frame, from LV base (upper left) to the apex (bottom right).

Linear regression analysis (Figure 4, top panels) between the automated technique and the manual reference volume values resulted in excellent correlation coefficients and regression slopes of 1 for both EDV and ESV (EDV: r=0.99, y=x+4; ESV: r=0.98, y=x-3.6). High correlation and regression slope near 1 were also obtained for EF (r=0.92, y=1.1x+0.03).

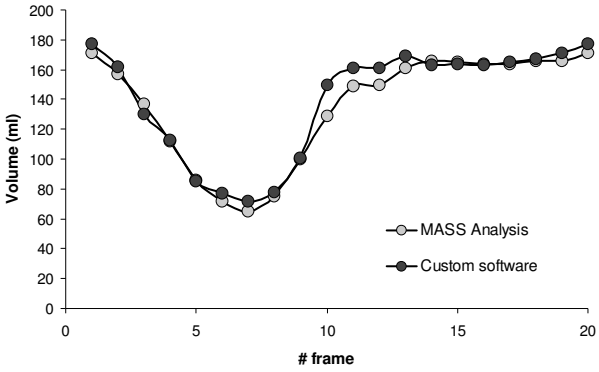

Figure 3. Example of LV volume time curves obtained in one patient, by manual tracing and custom software

Bland-Altman analysis (Figure 4, bottom panels) showed no significant biases between the automated measurements and the manual reference technique for EDV, ESV and EF (bias: 1ml; -3ml; 2%, respectively). These biases reflected systematic errors of 0.9%, -3.8% and 4.2% of the corresponding mean values. The 95% limits of agreement were relatively narrow (EDV: 10ml; ESV: 14ml; EF: 11%), providing additional support to the tight agreement between the two techniques. The calculated percent discordance was only 6.2±1.2%.

4. Discussion and conclusions

CMR imaging has become the reference technique for accurate measurements of LV volumes and function. In clinical practice, the extraction of these parameters is performed by manually tracing LV endocardial contours frame-by-frame on each slice and by the application of geometric modeling. New, efficient and robust algorithms need to be developed and tested for automated frame-by-frame endocardial contour detection from dynamic CMR images to become feasible in the majority of patients.

In this paper we described a technique representing a case of the minimal partition problem that can be formulated and solved using the level set method [8,9]. Many approaches based on non-linear partial differential equations and level set techniques have been used to solve segmentation problems. Our model allows us to detect objects with boundaries that are either not necessarily defined by a gradient or are very smooth, thus rendering the classical active contour models useless. In addition, our model can be applied to a variety of images once the statistical distribution of noise in the image is known [10,11], with no need for a priori knowledge of the shape of the objects to be detected. Importantly, only one parameter needs to be set in the model and it allows choosing the maximum curvature admissible in the segmentation: the regularization term that depends on this parameter prevents the “rupture” of the interface.

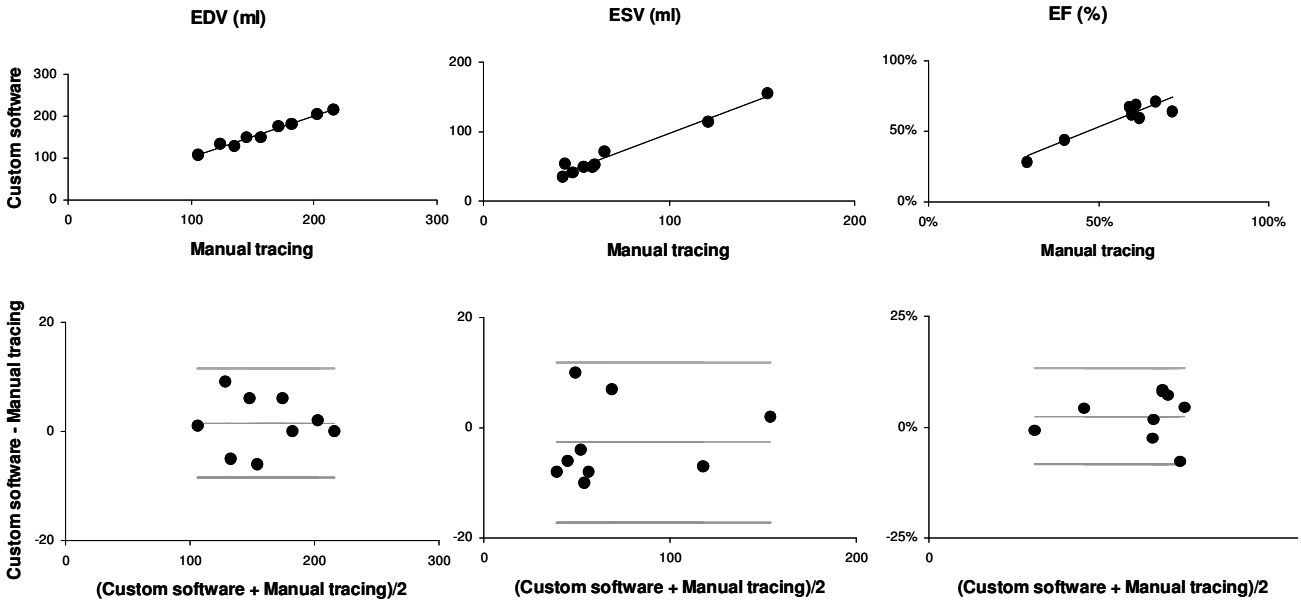

Figure 4. Linear regression (top) and Bland-Altman (bottom) analyses of LV EDV, ESV and EF obtained by the automated technique compared to the standard manual reference technique.

The use of the disk-area summation method for volume computation could be viewed as a limitation of this study. However, this method is routinely used in clinical practice and is considered the gold standard for LV volume measurements.

In summary, the proposed approach is considerably faster than manual tracing since the interactive part of the procedure consists of selection of one point inside the LV cavity, while border detection throughout the cardiac cycle is fully automated. In this initial feasibility study, this technique was found highly accurate compared to the standard reference methodology. Further testing in larger groups of patients is necessary.

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