Development and Validation of Automated Endocardial and Epicardial Contour Detection for MRI Volumetric and Wall Motion Analysis

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Abstract

Dynamic, ECG-gated, steady-state free precession short-axis images were obtained (GE Healthcare, 1.5T) in 8–12 slices in 15 patients with previous myocardial infarction. An expert cardiologist provided the reference values for: 1) left ventricular (LV) volumes and mass, by manually tracing endo and epicardial contours; 2) regional wall motion (WM) interpretation, by grading (normal, abnormal) three slices selected at apical, mid and basal level. Custom software based on image noise distribution and on image gradient was applied, from which end-diastolic (ED) and end-systolic (ES) volumes and mass were computed, as well as regional fractional area change (RFAC), from which automated classification of regional WM abnormality was defined. Comparison with reference values was performed by: 1) linear regression and Bland-Altman analyses for LV volumes and mass; 2) levels of agreement between the cardiologist WM grades and the automated classification. Optimal correlations (r^2>.97) and no bias were found for ED and ES volumes, while LV mass resulted in a good correlation (ED: r^2=.81; ES: r^2=.74) with a minimal overestimation (ED: 15.2g; ES: 8.7g) and narrow 95% limits of agreement (ED: ±30g; ES: ±33g). The automated interpretation resulted in high sensitivity, specificity, and accuracy (78%, 85%, 82%, respectively) of WM abnormalities. Combined automated endo and epicardial border detection from MRI images provides reliable measurements of LV dimensions and regional WM classification.

1. Introduction

Cardiac magnetic resonance imaging (CMRI) is a non invasive imaging modality with excellent spatial and contrast resolution. For these characteristics, it has become the standard reference for the assessment of left ventricular (LV) size and mass, as well as for the diagnosis of regional LV dysfunction [1,2].

Commercial software analysis packages for continuous measurement of LV volume and mass require slice-by-slice, phase-by-phase detection of endo and epicardial boundaries, and require extensive manual corrections, thus resulting in a semi-automated at best, time consuming, cumbersome, and subjective analysis technique. Moreover, visual interpretation of cine images suffers from inter-observer variability.

Availability of a reliable technique for automated detection of the endocardial and epicardial boundaries throughout the cardiac cycle would overcome this limitation and thus improve the accuracy of CMRI quantification of LV size, mass and function. Moreover, regional LV volume over time curves may provide clinically important information on regional LV function [3], beyond the traditional end-systolic and end-diastolic volumes (ESV, EDV), and global ejection fraction (EF), and additional insight into regional LV dysfunction.

Accordingly, our aim was to develop and test a new technique for combined automated endocardial and epicardial border detection from CMRI images throughout the cardiac cycle, and to validate it against manual reference measurements for global LV EDV, ESV, EF, mass, as well as regional wall motion abnormalities detection.

2. Methods

2.1. MRI imaging

A group of 15 patients with previous myocardial infarction, manifesting regional WM abnormalities, was recruited for this study.

CMRI was performed using a 1.5 Tesla scanner (Signa Hdx, GE Healthcare, Milwaukee, WI). An eight-element cardiac phased-array receiver surface coil with breath-

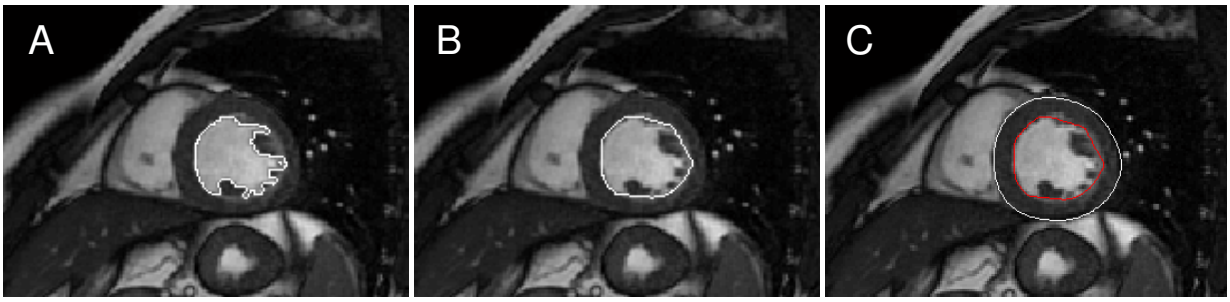

Figure 1. LV endocardial boundary is detected using a region-based level set technique taking into account the local noise patterns (A and B). Then, the epicardial boundary is detected using classical edge-based level-set model that searches from the endocardial boundary outwards (C).

holding in expiration and ECG-gating was used for signal reception. Three standard cine long-axis slices and a stack (from 8 to 12) of contiguous cine short-axis slices from the atrio-ventricular ring to the apex were acquired using a steady-state free-precession pulse sequence (30 phases, slice thickness 8 mm with no overlap and no gap, FOV= 40 cm, reconstruction matrix 256 x 256, TR= 3.5 ms, TE=1.5 ms, flip angle 45°).

2.2. Reference technique

CMRI data were analyzed using commercial software (MASS 6.1, Medis, Leiden, Netherlands) installed on the MRI workstation. An expert cardiologist proceeded into the conventional analysis of these images, by manual tracing LV endo and epicardial contours. Then, LV ED and ES volumes and mass were measured using standard volumetric techniques.

Moreover, dynamic images were reviewed and regional WM was interpreted in three slices selected at apical, mid and basal level. In each of these slices, the six regional segments (anterior, lateral, antero-lateral, septal, inferior, posterior) [4] were qualitatively graded as normal or abnormal, thus providing the "gold standard" for WM interpretation.

2.3. Automated technique

Custom software based on region-based image noise distribution (for LV endocardial detection) and on edge-based image gradient (for LV epicardial detection) was applied throughout the cardiac cycle for each frame and slice.

The endocardial border detection required the manual placement of a single point inside the LV cavity in a single frame. In this frame the endocardial boundary was automatically detected (figures 1A and 1B). Our approach was based on the assumption that noise distribution in the blood pool is different from that in the myocardium. This assumption allowed us to partition the heart into maximally homogeneous regions taking into account the local noise patterns [5]. From a mathematical point of view, we defined a curve C, centered in the manual selected point, as the zero level set of an implicit real function φ taking values on the image domain Ω:

$$C = \{(x, y) \in \Omega: \varphi(x, y) = 0\}$$

This initial circumference C undergoes an evolution in order to maximize the following functional *F*:

$$F(I,C) = \varepsilon \cdot lenght(C) + \int_{\Omega_i(C)} \log p(I)\, dxdy + \int_{\Omega_o(C)} \log p(I)\, dxdy$$

I is the gray level intensity image, $\Omega_i(C)$ and $\Omega_o(C)$ are the regions inside and outside *C*, and $\varepsilon \cdot length(C)$ is a regularization term [6]. *p(I)* represents the probability density distribution of the gray levels in MRI images, which can be approximated with a Gaussian distribution under fairly reasonable conditions (figure 1A).

Following this step, the boundary regularization was achieved using curvature motion [7] not allowing curvature above certain level and designed to automatically include the papillary muscles in the LV cavity (figure 1B).

To identify the epicardial boundary (figure 1C) we drove the evolution of an initial contour applying the well-known Malladi-Sethian model for active contour evolution. The model includes a dependence of the speed on the curvature, a propagation expansion speed and an advection speed based on the image gradient [8]:

$$\partial_t \phi = g(\varepsilon K - 1)|\nabla \phi| + \nu \nabla g \cdot \nabla \phi$$

with adequate boundary conditions and the previously computed endocardium contour as initial condition.

At the end of this step, the epicardium boundary was also regularized applying a modified curvature motion.

2.3.1. LV volume and mass quantification

For endocardial detection, the region-based approach was selected, and applied from basal to apical slices for each frame. In the basal slice (s), after initialization of the algorithm's parameters (radius of the initial circle, and % of radius decrement from one slice to the next one), the

operator selected one point inside the LV cavity. Then, automatically, the applied algorithm expanded the initial circle according to the videointensity probability distribution followed by the regularizing expansion to include the papillary muscles, when present. The algorithm used the detected contour on the slice s as initialization for the next (s+1) slice, after reducing it by the % set by the operator.

For epicardial detection, this approach required a robust initialization on the first frame f. The operator has two choices in order to provide the contour initialization: 1) use the previously detected endocardial contour dilated by a proper morphological operator with a structuring element of user-defined size; 2) manually initialize the contour close to the epicardium. For the next frame f+1, the initialization is obtained applying the "erode" morphological operation applied to the epicardial contour on the frame f.

For each slice and frames, the detected contours were then superimposed to the original image, to allow for possible corrections, if needed.

Then, the LV volume was automatically computed by summing the LV area in each slice (measured as pixel counts inside the endocardial contour) multiplied by the pixel spatial resolution and by the slice thickness (from the DICOM header). In the same way, the LV mass was computed as the difference between the LV epicardial and LV endocardial volumes, and multiplied by 1.05 to be expressed in grams. The same number of slices included for the reference value assessment by the expert were included in these computations, to avoid bias due to the inclusion of a different number of slices.

For the automated interpretation of regional WM, the ED frame was used to define the standard segmentation scheme for the LV short-axis view in each slice [4]. In the slice at mid-ventricular position, the ED centroid of the LV cavity was calculated and used as the origin of segmentation. An additional point was then manually placed at the junction between the right ventricular free wall and the interventricular septum. Starting from that point, the LV cavity was divided into six 60◦ wedge-shaped segments, corresponding to those used for visual assessment and grading of WM. For each segment, regional fractional area (RFA) in % of regional end-diastolic area was automatically calculated throughout the cardiac cycle using a fixed-coordinate reference system. From these 6 curves in each slice, RFA change (RFAC) was computed as the difference between the maximum and minimum value of RFA, expressed in % of the regional end-diastolic area. For each segment, these values were used to automatically interpret WM as normal (RFAC>=50%) or abnormal (RFAC<50%).

2.3.2. Statistical analysis

The results obtained from the automated analysis were then compared with the reference values by: 1) linear regression and Bland-Altman analyses for LV volumes and mass; 2) levels of agreement between the cardiologist WM grades and the automated classification of regional WM.

Sensitivity, specificity and accuracy for the automated interpretation of WM were also computed.

3. Results

Of the 15 patients, two were excluded for the presence of artefacts in the images that precluded correct performance of the developed algorithm without heavy manual correction. The automated analysis was then feasible in 13/15 (87%) patients.

The time required to process a single frame (ED or ES) from base to apex, for the detection of both endo- and epicardial contours, was approximately 1 min using a standard personal computer.

An example of the detected endo and epicardial contours for ED and ES frames at three levels of the LV is shown in figure 2.

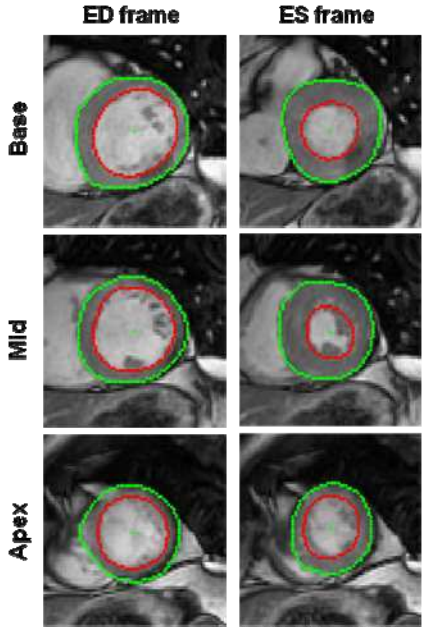

Figure 2. Detected endo and epicardial contours for ED and ES frames at three levels of the LV long axis.

Good correlations were found with the reference values for LV EDV ($y = 0.99x + 5.1$, $r^2=0.99$), and ESV ($y = x + 4.34$, $r^2= 0.99$), as well as with their derived parameters SV ($y = 0.98x – 0.24$, $r^2=0.97$) and EF ($y = x - 1.56$, $r^2=0.98$). For LV mass, a good correlation was found (ED, $y = 1.07x + 5.41$, $r^2=.81$; ES, $y = 0.97x + 12.86$, $r^2=0.74$).

Bland-Altman analysis resulted in minimal bias and

narrow limits of agreement in LV ED and ES volumes, and derived parameters. On the contrary, a significant overestimation and wider limits of agreement were found for LV mass. In particular, the bias expressed as error%/mean of the gold standard values resulted less than 10% in all the parameters, except ED LV mass (Table1).

Table 1. Results of the Bland-Altman analysis.

	Bias	**Bias as error%/mean**	**95% Limits of agreement**
EDV	- 2.5 ml	-1.4%	-17.7 ÷ 12.7 ml
ESV	-4.2 ml	-4.1%	-15.3 ÷ 6.8 ml
SV	1.7 ml	2.1%	-7.6 ÷ 11.0 ml
EF%	1.5 %	3.2%	-3.2 ÷ 6.2 %
ED mass	-15.2 g *	-11.2%	-44.9 ÷ 14.6 g
ES mass	- 8.7 g*	-5.8%	-41.3 ÷ 23.8 g

*: $p<.05$ vs null (paired t-test)

As regards the automated detection of LV wall motion, the time needed to process a single slice (30 frames), for the detection of the endocardial contour, and for the following regional analysis, was approximately 1 min. The gold standard interpretation resulted in 135 segments evaluated as normal, and 99 as abnormal.

Of the analyzed 234 segments (13 patients x 6 sectors x 3 slices), 77 were automatically classified as true positive, 115 as true negative, 20 as false positive and 22 as false negative, based on the selected 50% threshold. These counts resulted in a sensitivity of 77.8%, specificity of 85.1% and accuracy of 82% in the automated interpretation of wall motion.

4. Discussion and Conclusion

CMRI imaging provides accurate measurements of LV volumes, EF and mass nevertheless the quantification of volumes is based on time-consuming manual tracing of endocardial and epicardial boundaries in multiple slices. The subjective nature of this procedure limits the reproducibility of volume measurements and consequently of the set of derived parameters. The proposed combined automated endocardial and epicardial border detection procedure overcomes these limitations by allowing manual intervention just to optimize the automated detected contours.

Despite this advantage the proposed approach was not completely reliable in several LV basal slices, due to the presence of the aorta. In this case, manual tracing was performed in order to provide a reliable contour

The technique could be easily applied to all frames in the cardiac cycle, on a different number of slices of fixed thickness for each frame.

Results on WM abnormalities detection could be also improved by optimizing the RFAC threshold by ROC analysis.

In conclusion, our results showed that volumetric analysis of CMRI data based on direct detection of endocardial and epicaldial boundaries is feasible and provides reliable measurements of LV dimensions and regional WM classification. The accuracy of this technique was demonstrated by the excellent agreement with the conventional methodology.

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