MODIFIED HOUGH TRANSFORM FOR LEFT VENTRICLE MYOCARDIUM SEGMENTATION IN 3-D ECHOCARDIOGRAM IMAGES

John E McManigle, Richard V Stebbing, J Alison Noble

BioMedIA Lab, Institute of Biomedical Engineering, Dept. of Eng. Science, University of Oxford

ABSTRACT

Segmentation of the left ventricular myocardium from 3D echocardiograms is complicated by speckle, artifact, and complex anatomy. Typical segmentation methods benefit from accurate initialization. We propose a two-step Hough transform to find an annular approximation of the myocardium in short-axis echo slices. The method was compared to manual segmentation of 5641 slices by center points and endocardial and epicardial radii. Centers deviated by a mean 3.31 mm, and radii by 2.57 mm and 3.04 mm, respectively. Dice's coefficient of similarity was 0.70. Similarity is higher when apical slices are ignored. 93.8% of all slices and 96.8% of non-apical slices met criteria that suggest they would be appropriate to initialize further segmentation.

Index Terms— Echocardiography, Image segmentation

1. INTRODUCTION

Automated segmentation of the left ventricular (LV) myocardium is an important first step in evaluating abnormalities in cardiac structure and motion. While blood pool segmentation alone allows the calculation of volumetric parameters (stroke volume, ejection fraction, etc.), other clinically important measurements, such as stress-strain, synchrony, and wall motion, require segmentation of the myocardium as well.

Traditional segmentation methods, such as active contours and level sets, have been used with some success in echocardiography. However, especially for images produced by current 3D ultrasound probes, low spatial resolution, speckle, shadowing, and parallel-beam effects cause spurious edge responses throughout the blood pool as well as missing edges [1]. As a result, traditional segmentation techniques are often misled. Initialization close to the appropriate boundaries is therefore critical for correct convergence [2]. Although shape priors have been used with varying success to overcome these obstacles, the resulting methods are constrained by the quality, quantity, and variety of training data available [3]. Segmentation of the epicardial boundary is further complicated by the presence of nearby tissues with similar echogenicity and proximity to the image edge [4, 5].

The circular Hough transform has been used to segment the LV blood pool from short-axis echocardiogram images without relying on specific shape priors. Bansod and Burkule used the local gradient direction of short-axis image pixels to simplify the circular Hough transform for approximation of the LV blood pool [6]. They took advantage of the typical clinical 2D+t echocardiogram scan window to find the LV center point.

Fernández-Caballero et. al. applied the elliptical Hough transform to short-axis images, using Derivative-of-Gaussian (DroG) as a smoothing and edge-detection operator. These short-axis segmentations were then used with a shape-based long-axis segmentation to initialize an active contour segmentation [7].

Here, we introduce a myocardial segmentation technique based on the circular Hough transform. By applying an extremely simple constraint – that the LV myocardium is approximated by an annulus in short-axis cross-section – a preliminary segmentation technique is developed which takes advantage of both endocardial and epicardial image information. The segmentations generated are compared to expert manual segmentation of 3D+t echocardiogram data and evaluated for their appropriateness to initialize a subsequent segmentation step.

2. METHODS

The Hough transform is a generalizable feature detection algorithm [8]. Originally used to find lines in bubble chamber photographs, the technique relies on an "accumulator" image in the parameter space of the feature to be detected (in the case of a line, θ and s) [9]. The accumulator facilitates a voting mechanism: As each pixel in the image is scanned, the accumulator is updated to reflect that image pixel's contribution to the likelihood that each feature defined in the space of the accumulator is present. After all image pixels are scanned, the maximum value of the accumulator represents the parameters of the highest-likelihood feature. We introduce a modified, two-step voting procedure to the circular Hough transform to perform a preliminary segmentation of the left ventricular myocardium.

Standard clinical 3D+t echocardiogram sequences are acquired. Two-dimensional short-axis slices are extracted and median-filtered as a pre-processing step. Each median-filtered short-axis slice is an input image I. To take advantage

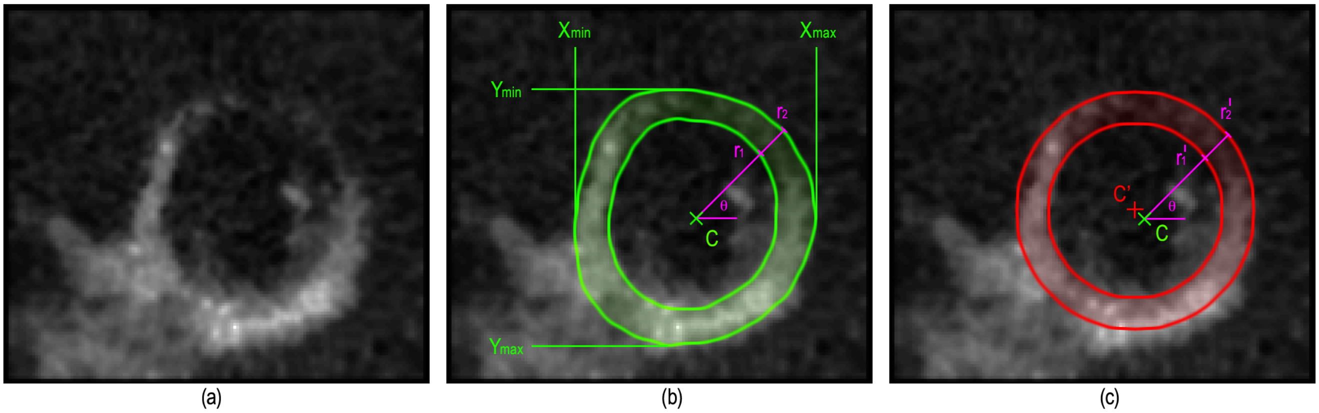

Fig. 1. Example of a manual and modified Hough transform segmentation and corresponding features for comparison. (a) Original short-axis slice from 3D echocardiogram frame. (b) Manual segmentation. Point C is defined as the center of the bounding box of the manual segmentation. Radii r_1 and r_2 are measured from C at eight angles θ. (c) Hough transform annular segmentation, and its center C'. For comparison, the radii r'_1 and r'_2 are measured from C, the manual segmentation center.

of the directional nature of the left ventricular cross-section (approximated by a bright ring in an otherwise dark field), orthogonal directional gradient images G_x and G_y are calculated using a first-order forward difference approximation.

In order to detect the approximately annular cross-section of the LV, a 3D accumulator image H is defined over the parameter space (c_x, c_y, r), where c_x and c_y define the x and y coordinates respectively of a potential circle center, and r is the radius of that circle. The value of each accumulator point is calculated by the sum:

$$H(c_x, c_y, r) = \sum_{\theta} \cos\theta \cdot G_x(x', y') + \sin\theta \cdot G_y(x', y')$$

$$\begin{cases} x' = c_x + r\cos\theta \\ y' = c_y + r\sin\theta \end{cases}$$

Accumulator values much greater than zero represent strong circular edges with bright pixels on the inside (e.g. an endocardial border), and values much less than zero represent edges with dark pixels on the inside (e.g. an epicardial border). The annulus of the left ventricular wall is described by these two concentric circles.

For each potential center (c_x, c_y), the best endocardial and epicardial radii r_1 and r_2, respectively, are:

$$r_1(c_x, c_y) = \arg\max_{r} H(c_x, c_y, r)$$
$$r_2(c_x, c_y) = \arg\min_{r>r_1} H(c_x, c_y, r)$$

The accumulator values at these radii are then used to assign each potential center a likelihood score s (Figure 2):

$$s(c_x, c_y) = k\,H(c_x, c_y, r_1) - H(c_x, c_y, r_2)$$

Where k is a constant (in practice, $k = 2$ works well). The annular approximation of the left ventricular myocardium in the given short-axis slice has the center (c_x, c_y) that maximizes s, and its corresponding radii $r_1(c_x, c_y)$ and $r_2(c_x, c_y)$.

3. EXPERIMENTS AND RESULTS

3.1. Data Set

Twenty-five 3D+t apical view echocardiograms were obtained from the John Radcliffe Hospital in Oxford. The subjects were healthy volunteers, and each study was recorded on a Philips iE33 ultrasound system. Spatial resolution was $0.88 \times 0.88 \times 0.81$ mm^3 and temporal resolution was on average 59 ms. Each 3D+t sequence consisted of between 11 and 20 3D frames, with the first frame at end diastole. The first 11 frames of each sequence were used in the experiments, for a total of 275 3D images.

Manual segmentation was performed by three experts: for each of the 3D images, one expert delineated the LV myocardium in every fifth short-axis slice of each volume. The expert recorded an epicardial and an endocardial contour, using the orthogonal long-axis view to guide each short-axis

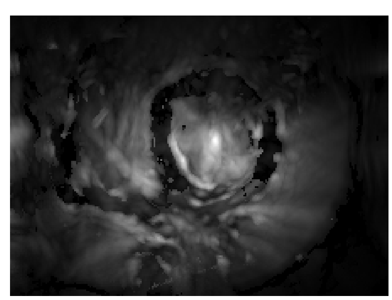

Fig. 2. Example of center likelihood score $s(c_x, c_y)$ map for a single short-axis slice. Bright indicates likely LV center.

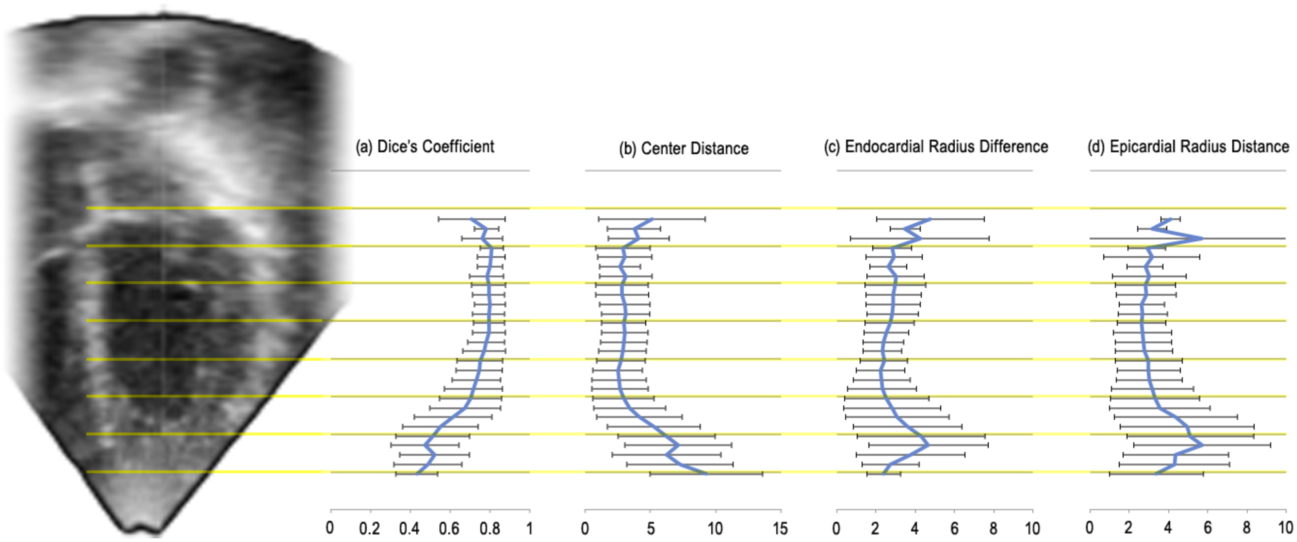

Fig. 3. Segmentation comparison by long-axis coordinate. Distances in pixels (1 px = 0.88 mm); error bars denote standard deviation. Accuracy is worse in the apical area, likely due to increased artifact and decreased contrast-to-noise ratio. (a) Dice's coefficient. (b) Distance ΔC between manual and Hough transform center points. (c) RMSD Δr_1 between manual and Hough transform endocardial radii over 8 angles. (d) RMSD Δr_2 between manual and Hough transform epicardial radii over 8 angles.

segmentation. Papillary muscles and valves were considered to belong to the blood pool. Where the myocardium was less visible due to shadowing, attenuation, or a parallel beam, expert knowledge of the shape of the heart wall, guided by orthogonal long-axis slices, was used to determine the boundaries. At the time of segmentation, the experts had no knowledge of the algorithm for comparison. Given the extent of the LV in each of the 275 3D images, a total of 5641 short-axis slices were used in the experiments.

3.2. Comparison Criteria

Parameter distance. For each of the 5641 short-axis slices, the center point C of the left ventricular cross-section was defined as the center of the bounding box of the manual segmentation (Figure 1). The distance ΔC between C and the center as calculated by the modified Hough transform, C', was measured.

For the eight angles $\theta = \frac{n\pi}{4}$, the endocardial and epicardial radii of the manual segmentation, r_1 and r_2 respectively, were measured. These were compared to the corresponding radii of the Hough transform segmentation, r_1' and r_2', which for comparison purposes were also measured from the manual segmentation center C (Figure 1). Comparison was by root mean square difference (RMSD) over the eight sets of radii measured in a given slice:

$$\Delta r_1 = \sqrt{\sum_\theta \left[r_1(\theta) - r_1'(\theta)\right]^2}$$

$$\Delta r_2 = \sqrt{\sum_\theta \left[r_2(\theta) - r_2'(\theta)\right]^2}$$

Dice's coefficient. For each slice, the manual segmentation M and modified Hough transform segmentation H of the LV myocardium were compared using Dice's coefficient d:

$$d = \frac{2 \cdot |M \cap H|}{|M| + |H|}$$

Initialization suitability. If the Hough transform segmentation is used to initialize a second, traditional segmentation step (e.g. level set or active contour method), that second step is more likely to converge if its boundary does not have to cross an image feature edge. Therefore, the Hough transform segmentation is more suitable to initialize a further segmentation if, for each radius measured:

1. $r_1' < r_2$, and
2. $r_2' > r_1$

These criteria were evaluated for each slice.

Table 1. Segmentation similarity measures (mean $\pm$ stdev)

	All Slices	**Basal 80%**
ΔC	3.31 ± 2.65 mm	2.65 ± 1.88 mm
Δr_1	2.57 ± 1.78 mm	2.34 ± 1.43 mm
Δr_2	3.04 ± 2.10 mm	2.68 ± 1.68 mm
Dice's d	0.70 ± 0.17	0.75 ± 0.13

3.3. Results

The results of the parameter distance and Dice's coefficient experiment are summarized in Figure 3. The quality of automatic segmentation is much higher in the basal area of the LV compared to the apical area, largely due to the lack of meaningful image data in apical short-axis slices. (Manual segmentation was performed with the benefit of long-axis slices.) Therefore, Table 1 summarizes the distance measurements and Dice's coefficient both for all slices evaluated, and for slices in the basal 80% of the LV. The center position and radii of the automated segmentations differed from the manual segmentations by about 3.0 mm across the entire ventricle, and about 2.6 mm when the low-image-quality apical region was excluded. Dice's coefficient was on average 0.70 and 0.75, respectively, across these regions.

The initialization suitability criteria were met by 93.8% of slice segmentations evaluated. When only the non-apical slices were considered, the criteria were met by 96.8% of segmentations.

4. CONCLUSION

Segmentations produced by the modified Hough transform method fit the criteria for initialization of a subsequent segmentation step in the majority of cases. This result was further improved when indistinct apical slices were ignored. The practical performance of these segmentations as an initialization step remains to be evaluated.

Even without further evolution, the segmentations produced by the modified Hough transform method produce features that differ from the gold-standard manual segmentation by an average of 2.5 - 3.0 mm. This compares with state-of-the-art techniques, which are capable of achieving accuracy in the range of 1.4 - 1.8 mm using methods that consider speckle statistics and myocardial tissue characteristics [4]. This suggests that even without further evolution, the modified Hough transform method may be useful for quickly estimating physiological parameters and basic LV shape information.

5. ACKNOWLEDGMENTS

The authors thank Michael Verhoek for his manual segmentation expertise.

This work was supported by the U.S. National Institutes of Health (NIH) Graduate Partnership Program (GPP) and the National Heart, Lung, and Blood Institute (NHLBI) Advanced Cardiovascular Imaging Group.

This work benefited from the use of the Insight Segmentation and Registration Toolkit (ITK), open source software developed as an initiative of the U.S. National Library of Medicine and available at www.itk.org.

6. REFERENCES

[1] J. A. Noble and D. Boukerroui, "Ultrasound image segmentation: a survey," *Medical Imaging, IEEE Transactions on*, vol. 25, no. 8, pp. 987–1010, 2006.

[2] Kashif Rajpoot, Vicente Grau, J. Alison Noble, Harald Becher, and Cezary Szmigielski, "The evaluation of single-view and multi-view fusion 3D echocardiography using image-driven segmentation and tracking," *Medical Image Analysis*, vol. 15, no. 4, pp. 514–528, Aug. 2011.

[3] Tobias Heimann and Hans-Peter Meinzer, "Statistical shape models for 3D medical image segmentation: A review," *Medical Image Analysis*, vol. 13, no. 4, pp. 543–563, Aug. 2009.

[4] Yun Zhu, Xenophon Papademetris, Albert J. Sinusas, and James S. Duncan, "A coupled deformable model for tracking myocardial borders from real-time echocardiography using an incompressibility constraint," *Medical Image Analysis*, vol. 14, no. 3, pp. 429–448, June 2010.

[5] Andriy Myronenko, Xubo Song, and David J. Sahn, "LV motion tracking from 3D echocardiography using textural and structural information," in *Proceedings of the 10th international conference on Medical image computing and computer-assisted intervention*, Berlin, Heidelberg, 2007, MICCAI'07, p. 428435, Springer-Verlag.

[6] P. Bansod, U. B Desai, and N. Burkule, "Automatic detection of left ventricle in echocardiographic sequences using radial search and temporal smoothing," in *2007 15th International Conference on Digital Signal Processing*. July 2007, pp. 139–142, IEEE.

[7] Antonio Fernndez-Caballero and Jos M. Vega-Riesco, "Determining heart parameters through left ventricular automatic segmentation for heart disease diagnosis," *Expert Syst. Appl.*, vol. 36, no. 2, pp. 22342249, Mar. 2009.

[8] D.H. Ballard, "Generalizing the hough transform to detect arbitrary shapes," *Pattern Recognition*, vol. 13, no. 2, pp. 111–122, 1981.

[9] Paul V. C. Hough, "Method and means for recognizing complex patterns," Dec. 1962, U.S. Classification: 382/281.