ULTRASOUND MYOCARDIAL TRACKING WITH SPECKLE REDUCING ANISOTROPIC DIFFUSION ASSISTED INITIALIZATION

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ABSTRACT

Cardiac parameters such as end-systolic volume, ejection fraction and myocardial mass are essential to the diagnosis and treatment of cardiovascular disease (CVD). Traditionally, these parameters are calculated based on manual myocardial segmentation by a trained technician. Fast, accurate, and automatic segmentation would provide researchers with an increased subject pool, an enhanced understanding of CVD, and may lead to the development of new therapies. In this paper we propose an automated algorithm for myocardial segmentation. This method utilizes speckle reducing anisotropic diffusion to assist the automated contour initialization. Speckle tracking segmentation (STS) is then applied throughout the cardiac cycle to track the myocardial borders. This approach, compared to standard active contour techniques, reduces the RMSE to ground truth by an order of magnitude.

Index Terms: Biomedical acoustics, Biomedical imaging, Biomedical image processing, Cardiovascular system, Correlation, Image segmentation

1. INTRODUCTION

Cardiovascular disease (CVD) accounts for 38% of all deaths in the United States, making it the number one killer in the nation [1]. An increase in the basic understanding of the progression from myocardial infarction (MI) to heart failure will lead to more accurate diagnosis and improved patient therapy. Clinicians and researchers are especially interested in cardiac physiological measurements such as ejection fraction (EF), myocardial mass, wall thickness, and wall thickness option for the measurement of these parameters [2].

Currently, clinicians and researchers manually delineate the endocardial and epicardial borders of the left

ventricle (LV) from ultrasound images at multiple phases throughout the cardiac cycle. This process is tedious, time consuming, and susceptible to intra- and inter-observer variability. An automated cardiac analysis tool would enable researchers to study larger patient populations and thereby improve the statistical significance of the data.

To date, several methods have been investigated to solve the segmentation problem. Active contours [3] have been explored, but are limited in ultrasonic applications due to poor edge contrast. Active shape models [4] have also been investigated, but require a comprehensive and cumbersome library of templates including all the various stages of post-MI cardiac remodeling. Tracking algorithms have been used to update contours through the cardiac cycle in MRI [5].

In this paper, we present an automated myocardial segmentation technique. We endeavor to segment both the endocardial and epicardial borders of the murine LV in ultrasound images obtained in short axis view. We first apply speckle reducing anisotropic diffusion (SRAD) [6] to smooth the image while preserving image edges. An edge-map of the smoothed image in combination with an elliptical Hough transform is used to coarsely localize the boundaries. We then use speckle tracking segmentation (STS), employing a normalized cross correlation technique, to track the myocardium by exploiting the stochastic properties of ultrasound imagery. Success is measured by the RMSE of our contours compared to ground truth.

2. METHOD AND THEORY

In this section we describe our myocardial segmentation method. We first present our initialization methods, including the theory behind SRAD and its use in our application. We then present the STS algorithm utilizing normalized cross correlation. Finally, we present additional filtering constraints to ensure the tracking of significant points.

2.1. SRAD assisted initialization

In order to initialize the myocardial borders in a short axis ultrasound image of a mouse heart, we first utilize SRAD [6]. SRAD smoothes homogeneous regions of ultrasound speckle while preserving true image edges. Thus, myocardial borders become more distinct and easier to locate.

In SRAD, for a given intensity image, I(x,y), the partial differential equation describing the output is

$$\partial I(x, y; t) / \partial t = div[c(q)\nabla I(x, y; t)], \qquad (1)$$

where [x,y] are the image coordinates, *t* is time, *div* is the divergence operator, ∇ is the gradient operator and c(q) is the diffusion coefficient defined as

$$c(q) = \left[1 + \frac{\left[q(x, y; t)^2 - q_0^2(t)\right]}{q_0^2(t)\left[1 + q_0^2(t)\right]}\right]^{-1}.$$
 (2)

This equation utilizes a discrete form of the instantaneous coefficient of variation (ICOV) [7], define as

$$q(x,y;t) = \sqrt{\frac{\left| (1/2)(\left| \nabla I \right| / I)^2 - (1/16)(\nabla^2 I / I)^2 \right|}{\left[I + (1/4)\nabla^2 I / I \right]^2}},$$
 (3)

where the speckle scale function, $q_0(t)$, is the coefficient of variation in a homogeneous region with well developed speckle.

After applying SRAD, an edge image is obtained by locating the zero crossings of the Laplacian of the intensity image. An example of an image processed with

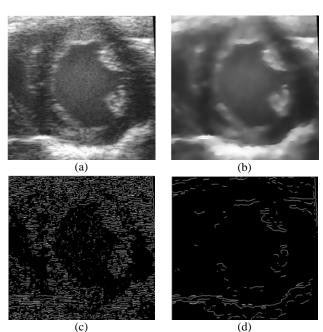


Fig. 1. Cardiac ultrasound (a,b) with edge map images (c,d) before (a,c) and after (b,d) SRAD

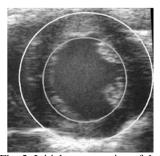


Fig. 2. Initial segmentation of the epicardial and endocardial borders

SRAD, with the corresponding edge maps before and after SRAD, is shown in Fig. 1. Note how SRAD eliminates a significant number of false edges caused solely by speckle.

The LV contours in the short axis view can be modeled as an ellipse [8], thus we utilize an elliptical Hough transform [9] to segment the initial epicardial and endocardial borders. We first search for the epicardial border, and then limit the endocardial search to regions within the epicardial boarder. A sample initialization is shown in Fig. 2.

2.2. Speckle tracking segmentation (STS)

To track the contour throughout the cardiac cycle, we exploit the stochastic properties of ultrasound speckle. Speckle remains relatively coherent from one frame to the next. Assuming local motion is small and is predominantly translational, we may thus track small regions of speckle using standard correlation techniques.

We first sample the initial contour into evenly spaced points. For each point, we store a small region of interest (ROI), and track the region throughout the cardiac cycle using normalized cross-correlation. We use the ROI from the last frame as a template, searching within a small window of the current image for the coordinates of maximal normalized cross-correlation. The template is periodically updated to correct for rotation and throughplane motion. Fig. 3 illustrates STS points in the first frame and the last frame of a sequence.

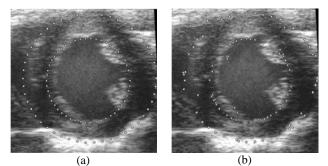


Fig. 3. STS results for (a) first and (b) last frame a cine image sequence of a cardiac cycle.

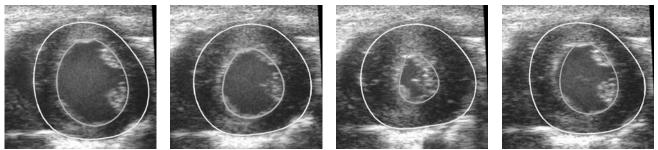


Fig. 4. Several tracked frames from a cardiac cycle using SRAD-assisted initialization and speckle tracking

2.3. STS filtering

After STS, we introduce two additional constraints to eliminate invalid tracking results. First, we assume that points on the myocardial borders should be in approximately the same location in the first and last frame of the sequence. We eliminate points when their net displacement between the first and last frame is greater than ε pixels, where ε is a small number. Additionally, points lying on well defined edges produce better tracking results over the cardiac cycle. We therefore eliminate points that have an ICOV value less than the mean image ICOV, indicating a strong well defined edge.

These two constraints provide a filtered set of points that more accurately describe myocardial movement. We fit a cubic spline to the remaining filtered point set to determine the final segmentation. Fig. 4 shows the segmentation result on several images in an example cardiac cycle.

3. RESULTS AND DISCUSSION

In this section we describe the techniques used to collect the data and validate the performance of STS with respect to those obtained manually and by way of active contour tracking. We also provide a discussion of the error between the manual and automatic tracking.

3.1. Imaging technique & data set

Mouse cardiac images were acquired using a VisualSonics Vevo770 scanner (VisualSonics Inc., Toronto, Ontario, Canada) at 35Mhz. Image sequences were retrospectively assembled into a representative heartbeat composed of over 100 frames per cardiac cycle using the Vevo's "ECG-based Kilohertz Visualization (EKV)" capability. C57BL/6 mice were used for our studies. Mice were held at 37° C +/- 1°C (monitored using a rectal temperature probe) using an electric heating pad and maintained supine under Isoflurane gas anesthesia. Images were processed in MATLAB [10] on a Pentium 4 processor (2.04 GHz) PC and 1 GB RAM.

Three data sets consisted of a 197 and two 104 image sequences of a cardiac cycle. The 104 image sequences

were obtained from the same mouse at different elevations along the LV. Ground truth was obtained by a trained technician segmenting both the endocardial and epicardial borders on 6 images spaced evenly throughout the cardiac cycle. Results are reported as the RMSE of automated segmentation results with respect to this manual segmentation. RMSE is reported in millimeters, where one millimeter is approximately 43 pixels for the 197 image sequence and 73 for the 104 image sequences.

3.2. Initialization results

We first analyzed the improvement in initialization accuracy with SRAD assistance. Initialization without SRAD on average leads to an RMSE relative to ground truth of 1.45 mm for the epicardial border and 1.58 mm for the endocardial border. SRAD assisted initialization on average reduces the RMSE relative to ground truth to 0.17 mm for the epicardial border and 0.12 mm for the endocardial border.

Fig. 5 illustrates initialization results without SRAD (a) and with SRAD (b). Without SRAD there are many false edges hindering Hough transform performance, which leads to poor initialization of the epicardial and endocardial borders.

3.3. Tracking results

We then analyzed the accuracy of the STS algorithm, comparing our results to an active contour segmentation [3] with a generalized gradient vector flow (GGVF) [11]

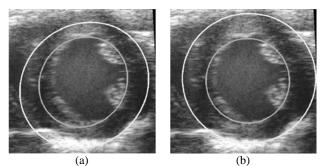


Fig. 5 - Initialization (a) without and (b) with SRAD



Fig. 6. First frame of an active contour segmentation

external force. The parameters used for this active contour were α =1 (tension), β =10 (rigidity), and k=0.05 (field smoothness weight). These parameters were set empirically to optimize the active contour accuracy. Fig. 6 illustrates the active contour segmentation of the first frame in a sequence.

Fig. 7 illustrates the RMSE values for STS and for the active contour algorithm using the SRAD assisted initialization. The active contour algorithm produces an average RMSE of 1.84 mm for the epicardial border and 1.71 mm for the endocardial border. STS reduces the average RMSE to 0.14 mm for the epicardial border and 0.17 mm for the endocardial border. Additionally, employing an active contour segmentation requires 110 seconds per frame, while using the proposed method requires only 50 seconds per frame.

3.4. Future work

Future work will focus on further refinement and constraint of the segmentation result. Using known cardiac biomechanical constraints, shape constraints can be used to improve the segmentation results. Furthermore, the correlation results can instead be used as a vector field in more advanced segmentation and tracking techniques.

4. CONCLUSION

In this paper we have developed an automated myocardial segmentation algorithm. Utilizing SRAD and an elliptical Hough transform, we are able to successfully initialize our segmentation. Compared to no filtering, SRAD filtering reduces the initialization RMSE by 88% for the epicardial border and by 92% for the endocardial border. We then use STS to provide an accurate and expeditious segmentation. Compared to a traditional active contour segmentation, STS reduces RMSE by 92% for the epicardial border and by 90% for the endocardial border.

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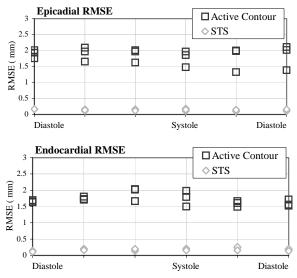


Fig. 7. STS and active contour tracking results for the epicardial (top) and endocardial (bottom) borders.

REFERENCES

- [1] "Heart Disease and Stroke Statistics 2005 Update," American Heart Association, Dallas, Texas 2005.
- [2] A. Webb, *Introduction to Biomedical Imaging*. Hoboken: John Wiley & Sons, Inc., 2003.
- [3] M. Kass, A. Witkin, and D. Terzopoulos, "Snakes Active Contour Models," *International Journal of Computer Vision*, vol. 1, pp. 321-331, 1987.
- [4] T. F. Cootes, C. J. Talyor, D. H. Cooper, and J. Graham, "Active Shape Models - Their Training and Applications," *Computer Vision and Image Understanding*, vol. 61, pp. 38-59, 1995.
- [5] B. S. Spottiswoode, X. Zhong, C. H. Lorenz, B. M. Mayosi, E. M. Meintjes, and F. H. Epstein, "Motionguided Segmentation of the Left Ventricle for Cine DENSE MRI," presented at Proc. 14th International Symposium for Magnetic Resonance in Medicine (ISMRM), USA, May 2005.
- [6] Y. Yu and S. T. Acton, "Speckle Reducing Anisotropic Diffusion," *IEEE Transactions on Image Processing*, vol. 11, pp. 1260, 2002.
- [7] Y. Yu and S. T. Acton, "Edge Detection in Ultrasound Imagery Using the Instantaneous Coefficient of Variation," *Image Processing, IEEE Transactions on*, vol. 13, pp. 1640, 2004.
- [8] A. D. McCulloch, "Cardiac Biomechanics," in *The Biomdeical Engineering Handbook*, J. D. Bronzino, Ed., 2nd ed. Boca Ration: CRC Press, LLC, 2000, pp. 28.1-28.26.
- [9] D. H. Ballard and C. M. Brown, *Computer Vision*. Englewood Cliffs: Prentice-Hall, Inc., 1982.
- [10] "MATLAB 7.1," The Mathworks, Inc., 2005.
- [11] C. Xu and J. L. Prince, "Generalized Gradient Vector Flow External Forces for Active Contours," *Signal Processing - An International Journal*, vol. 71, pp. 131, 1998.