Cardiac Boundary Extraction on Echocardiographic Images Using Directed Graph *

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Abstract

Cardiac boundary extraction on echocardiographic images is essential for quantification of cardiac function. Tracing the endocardial boundaries on the end-diastolic and end-systolic images allows the computation of clinically important measures such as ejection rate. It is a clinical need for automatically detecting the borders. In this paper, we proposed a new approach for cardiac boundary extraction on echocardiographic images by directed graph. In this approach, we spread the cardiac image in the circular direction. The spread image is mapping to a directed graph. The shortest path is found by the dynamic programming algorithm. From the implemented results, we can obtain pretty good approximation for cardiac boundary extraction.

Keywords: Echocardiographic Image, Edge Detection, Directed Graph, Shortest Path

1 Introduction

Digital two-dimensional echocardiography is an ultrasonic imaging technique that is an important tool for cardiac imaging in attractive attributes of noninvasive, portability, and low cost. Cardiac boundary extraction on echocardiographic images is essential for quantification of cardiac function. The endocardial and epicardial boundaries of the Left Ventricle (LV) are useful quantitative

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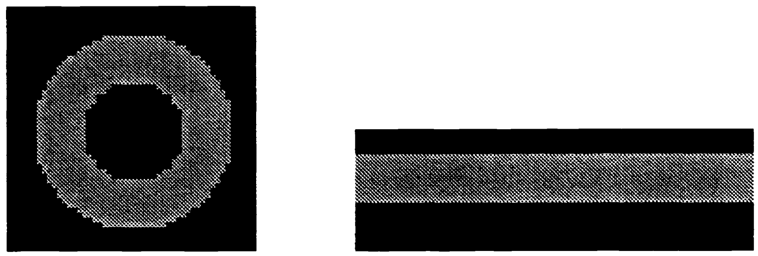
measure for various cardiac functions such as pressure-volume ratio, ejection fraction and cardiac wall motion. To quantify these measures, the contours of the LV need to be extracted. Manual tracing of the cardiac boundary is a time consuming and tedious task. It is a clinical need for automatically detecting the borders.

Boundary detection in an ultrasound image is a very difficult task. The edge detection in echocardiographic images presents some challenging difficult because of the inherent characteristics of the echocardiographic images, including blur, low contrast, speckle noise, and signal dropouts. A typical boundary detection procedure in echocardiography studies has three steps [1], preprocessing by smoothing, enhancing, and identifying. Chu et al. [2] proposed an algorithm based on the nonpurposive segmentation approach which consists of three steps, edge detecting, edge estimation, and nonlinearly edge processing. Coppini et al. [3] proposed an approach to extract left ventricle border including three step, edge detecting, edge grouping, and edge classification. Kass et al. [4] proposed the active contour model, known as Snake, to build a deformable contour which consists of connected spline segments and approximates to a desired form by minimizing an energy function which consist of internal, image, and constraint energy. The Snake model has been applied to medical image segmentation in variety of modalities. The Snake model needs an initial contour of border which is generally obtained by manual input. Recently, Ono and Ogawa [7] use the circularly spread image and a neural network to do segmentation in an MR image. They transformed the original image to a spread image. The segmentation task was converted to finding a polygonal line which divided the spread images to upper and lower halves. The polygonal line was determined by a neural network.

In this paper, we present a spread image approach for cardiac boundary extraction on echocardiographic images. The original image is transform to a spread image. A weighted directed graph is then constructed from the spread image. The weight of the vertices in the graph depend on both the first and second derivative edge detectors. There is weight on each edge as well. The weight is designed to describe the relationship between consecutive vertices in the graph. We then find the shortest path using dynamic programming . The shortest path corresponds to the endocardial boundary in the original image. The details of the algorithm are presented in the next section. The experimental results are shown in Section 3. We have conclusion in Section 4.

2 Method

In this section, we present the proposed approach to extract the cardiac border. There are 3 steps in the proposed approach namely, constructing the spread



(a) (b)

Figure 1: (a) original cardiac image (b) spread image from (a).

image from the original image, constructing the directed graph from the spread image, and finally finding the shortest path corresponding the endocardial wall in the original image.

2.1 Construct the Spread Image

A spread image, T, is produced from an original image O. Let c be the center of O. There are m radial lines emitting from c toward the boundary of O. Suppose the radial lines are ordered according the polar angle. The radial lines in order are mapped into m columns in T. Each radial line samples n points. Let r be the unit vector along the ith radial line. The n sampled points are $\{c + kr | k = 0 \ldots n-1\}$. These sampled points are the n elements in the ith column of T. The coordinate of a transformed spread image can be presented as a function of the coordinates of the original image as the following equation:

$$T(x, y) = O(y \cdot \cos(x), y \cdot \sin(x)), 1 \leq x \leq m, 1 \leq y \leq n, \tag{1}$$

where $T(x,y)$ and $O(x,y)$ is the intensity of coordinate (x,y) in spread and original images, respectively, and m and n are the image size of column and row of spread image, respectively. If $O(x,y)$ doesn't locate at grid point, bi-linear interpolation will be used to determine it. For example, the original image and the spread images are shown in Figure 1. From bottom to up, the spread image has three layers: fluid, soft tissue, and background.

In our experiment, the cardiac boundary on the spread image is a horizontal line from left to right. The border line can be traced from the leftest column to the rightest column.

2.2 Construct the Weighted Directed Graph

The weighted directed graph, $G(V, E)$, is constructed using the spread image. The vertex V is the union of the vertex sets V_i, $i = 0, \ldots, m$ where each vertex in V_i corresponds to a pixel in the ith column in the spread image. V_m corresponds to the firts column in the spread image. Each vertex in V_i has n directed edge connecting to all of the vertices in V_{i+1}. The jth vertex in V_i is denoted v_{i_j}. Since the vertex v_{i_j} can only connect to a vertex in V_{i+1}, the directed edge connecting v_{i_j} and the kth vertex in V_{i+1} is denoted $e_{i_{(j,k)}}$. The number of vertices and the number of edges are respectively $m \cdot n$ and $m \cdot n^2$.

There are weights associated with all the vertices and all the edges. The weights are designed so that the shortest directed path from v_{0_j} to v_{m_j}, for all j, corresponds to endocardial wall in the image.

The weights on the vertex v_{i_j} and edge $e_{i_{(j,k)}}$, denoted $w(v_{i_j})$ and $w(e_{i_{(j,k)}})$ are determined as the following equations,

$$w(v_{i_j}) = (-MH(v_{i_j}) - Sobel(v_{i_j})) \cdot \sin(GD(v_{i_j}),$$
$$w(e_{i_{j,k}}) = (j-k)^2,$$

where $MH(v_{ij})$ and $Sobel(v_{ij})$ are the magnitude of Marr-Hildreth and Sobel filters on v_{i_j}, respectively, and $GD(v_{ij})$ is the gradient direction on v_{i_j}.

Marr and Hildreth's theory [8] is filtered an image by a Laplacian-of-Gaussian (LoG) kernel

$$LoG(r) = \nabla^2 G(r) = \frac{-1}{2\pi\sigma^4}\left[2 - \frac{r^2}{\sigma^2}\right] exp\left(-\frac{r^2}{2\sigma^2}\right) \tag{2}$$

where $r = \sqrt{x^2+y^2}$ is the distance from the mask center, $G(r) = \frac{1}{2\pi\sigma^2} exp\left(-\frac{r^2}{2\sigma^2}\right)$ is an isotropic 2-D Gaussian, and σ is its standard deviation. The Laplacian ∇^2 is a second-order differential operator, edge points are individuated by the zero-crossing of the filtered image. The combination of ∇^2 with a Gaussian mask permits the smoothing out the noise, which is controlled by the σ parameter; the larger σ, the stronger the blurring. The cost of a vertex is inversely related to the likelihood that an edge is presented at that point. The likelihood value is then converted to a cost that the greater the edge strength, the lower the cost of the vertex. The Sobel's and Marr-Hildreth's filters are used for edge points detection. The term of gradient direction is the consideration of a priori knowledgement that classify which border we want. In the case of cardiac border extraction, Fig. 1 shows two borders in the spread image. The different border has different gradient direction. The correct gradient direction is needed to improve performance. In the echocardiographic image, the intensity of fluid region is lower than soft tissue. The gradient direction of endocardial border is 90 degree, so $\cos(GD)$ can be used for endocardial border classification.

2.3 Calculate the Shortest Path

With the weighted directed graph G available, we find the shortest path among the paths from v_{0_j} to v_{m_j}, $0 \leq j < n$. The shortest is a path that the total weight of the vertices and the edges on the path is minimized. The shortest path can be calculated using Dynamic Programming. Since an directed edge connects a vertex in V_i to a vertex in V_{i+1}, a path from v_{0_j} to v_{m_j} passes exactly a vertex in each V_i, $i = 0, \ldots, m$. Suppose that there is a shortest path from v_{0_j} to a vertex in V_i, say $v_{i_{j'}}$. The weight of the path is

$$\mathrm{Weightofthepathfrom} v_{0_j} tov_{i-1_k} + w(e_{i-1_{(k,j')}}) + w(v_{i_{j'}}).$$

Since the path from v_{0_j} to $v_{i_{j'}}$ is optimal, the path from v_{0_j} to v_{i-1_k} must be optimal. Thus, the shortest from v_{0_j} to $v_{i_{j'}}$ is

$$\min_{0 \leq k < n} \{\text{shortest path from } v_{0_j} \text{ to } v_{i-1_k} + w(e_{i-1_{(k,j')}} + w(v_{i_{j'}}).\} \tag{3}$$

Since a vertex v_{i+1_j} has n incoming edges which come from all the vertices in V_i. We can use a "sweep" algorithm to implement Equation 3 as the follows. Consider the case that we calculate the shortest path from v_{0_j} to v_{m_j}. The shortest pathes from v_{0_j} to the vertices in the V_1 can be easily calculated. Suppose that the shortest path from v_{0_j} to all of the vertices in V_i, $i \geq 1$ are available. The optimal path lengths from v_{0_j} to the vertices in V_{i+1} are calculated as the following. Let $v_{(i+1)_k}$ be a vertex in V_{i+1}. $v_{(i+1)_k}$ has incoming edges from all of the vertices in V_i, and the optimal path length from v_{0_j} to vertices in V_i are known. The optimal path length from v_{0_j} can be calculated using Equation 3.

3 Result

The proposed method has been tested by using a data set acquired from a rabbit heart. The volume of the heart chamber at the time that the images were acquired is known. A transthoracic transducer was used to acquired sequence of heart images with pull-back technique to obtain a set of 9 parallel cross sections. There are 24 sets of data to cover a cardiac cycle.

In this experiment, the size of original images is 200×170. We transfer the original image into a spread image which size is 360×170. The weighted, directed graph is constructed with 61200 vertices and 10115000 edges. The standard deviation of Gaussian filter is 8 pixel.

Fig. 2 shows four of the results of the cardiac boundary extraction on the data set by the proposed method. The results demonstrate that we provide pretty good approximation for the cardiac boundary by the proposed approach. When we extract the cardiac boundary of whole set of cardiac graphic images, we can calculate the cardiac volumes in whole cardiac cycle. If we compare the cardiac volume in the end -diastolic and end-systolic images, the ejection rate can be calculated.

4 Conclusion

In this paper, we proposed a new approach for cardiac boundary extraction on echocardiographic images using a directed graph. In this approach, we spread the cardiac image in the circular direction. The spread image is mapping to a directed graph. The shortest path is found by the dynamic programming algorithm. From the implemented results, we can obtain pretty good approximation for cardiac boundary extraction.

A problem with this approach occurs when the area of interest is not convev. In this case, we can not construct the corresponding directed graph. We pose this as a future work.

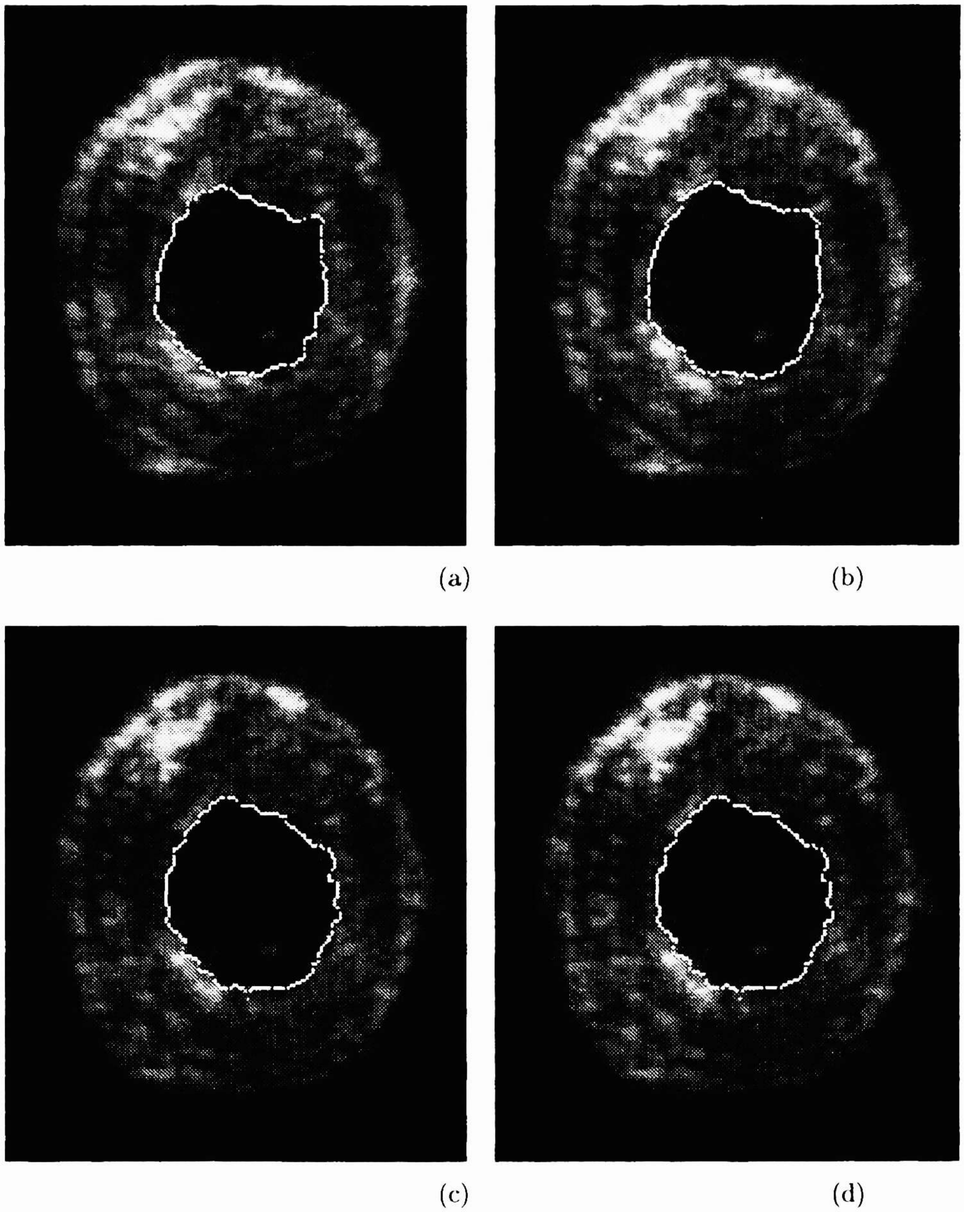


Figure 2: The results of cardiac border extraction

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