Almost Automatic Method for Reconstruction 3D Geometric Model of the Left Ventricle from 3D + 1D Precordial Echocardiogram

Yu-Tai Ching[a] Yu-Hsian Liu [a] Chwen-Liang Chang[a] and James S. J. Chen [b]

[a]Department of Computer and Information Science, National Chiao Tung University Hsinchu, Taiwan

[b]Department of Radiology, National Taiwan University, Taipei, Taiwan

ABSTRACT

Echocardiography is the most convenient means for both physicians and patients for heart disease diagnosis. The 3D+1D echocardiogram provides important information for evaluation of the 3D heart function such as the ejection fraction or wall motion. The most basic task to evaluate such functions of a heart is to segment left ventricles and reconstruct the the 3D geometric model of left ventricle from a set of echocardiographic images. Since there are many images involved, the method should not need too many user assists. In this work, we design a method for reconstructing the left ventricles with very few user assists.

Key Words Echocardiogram, 3D Model, Left Ventricle, snake model, α-shape, graph algorithm.

1. INTRODUCTION

Echocardiogram is one of the most important tool in cardiac disease diagnosis. It has the advantages of low cost, convenient, and non-toxicity. The 3D + 1D echocardiogram is available at present time. This technique provides 4D information of a heart. Using such information, it is possible for us to construct the 3D geometric model of heart chambers in a cardiac cycle. We then can calculate the ejection fraction or study the wall motion using the 3D model. In this work, we construct 3D geometric model from a set of 3D+1D precordial echocardiogram. The images were obtained using the rotational scanning technique. A pair of consecutive planes are 10 degree apart. There are 18 planes. Each plane consists of 25 to 30 images to cover a cardiac cycle. A potential difficulty to extract information from the data is due to the number of images involved. There are generally more than one hundred images in a set of 3D + 1D images. Since huge number of images involved, any approach that needs many user assists is infeasible. In this work, we propose an almost automatic method to segment the Left Ventricle from a set of 3D+1D precordial echocardiogram with very few user assists. We then construct the 3D geometric model of a left ventricle from the segmented results.

The proposed method consists of four steps

1. The speckle noises in an echocardiogram make the segmentation of a heart chamber difficult. The first step is to reduce the speckle noise using the SM filter.
2. The second step is to find the contour for the boundary of the left ventricle in each image. We first determine the heart chambers by intensity thresholding of images after SM filtering. The contour for the boundary of the heart chamber is then obtained by a two-step α-shape calculation. In order to obtained a better approximation for the wall, the contour is revised using the active contour method.
3. There are cases that the left ventricle and the left atrium become a chamber. Physicians generally separate these two chambers by connecting the base points of the mitral valve. The third step is to determine the mitral annular lines that divides the connected chamber into two. We present an almost automatic method to determine the mitral annular lines. Step 2 and step 3 need to a point in the left ventricle all the time in a plane.

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4. The 3D geometric model is then reconstructed from the contours obtained from the steps above.

2. METHODS

In this section, we describe the methods used in each step.

2.1. PREPROCESSING

The ultrasound images contain speckle noise. To reduce the speckle noise, we used a single-adaptive filter. The single-adaptive filter, which does not like the Mean Filter to smooth all signals in the image, abates noise and strengths the signal of the area having similar intensity [6,7].

Given a $W \times W$ window around the pixel (k, l). The output of the filter denoted $\hat{s}(k, l)$ is obtained using the following equation,

$$\hat{s}(k,l) = \hat{s}_{\mathrm{ML}}(k,l) + \beta(k,l)[x(k,l) - \hat{s}_{\mathrm{ML}}(k,l)]. \tag{1}$$

In Eq (1), $x(k, l)$ is the intensity of the pixel (k, l).

$$\hat{s}_{\mathrm{ML}} = \frac{\sqrt{\pi}}{2}\sqrt{\frac{1}{N}\sum_{W} x^2(k-i, l-j)} \tag{2}$$

is the local estimation for the original signal of (k, l). And the value of $\beta(k, l)$, which is ranged over [0,1], is given by

$$\beta(k,l) = 1 - \left(\frac{4-\pi}{4}\right)\frac{Ew[x^2]}{Ew[(x - \hat{s}_{\mathrm{ML}})^2]}, \tag{3}$$

where $Ew[x^2] = \frac{1}{N}\sum_{j=1}^{N} x_i^2$. If $\beta(k, l) = 0$, (k, l) is considered a noise point and its intensity is altered by the local observation.

2.2. CALCULATE THE CONTOUR FOR THE BOUNDARY OF LEFT VENTRICLE

In this section, we present the method to calculate the contour for the boundary of the left ventricle. The heart chamber in an echocardiogram generally has lower intensity. We use a 2-means algorithm to determine the low intensity pixels in the image after applying the SM filter. In order to calculate the boundaries for these pixels, we use an α-shape technique.

α-shape defines the shapes of sparse points in space. The shape of a set of points depends on α. For the case that $\alpha = 0$, the shape consists of a set of disconnected points. If $\alpha = \infty$, the shape of the set of points is the convex hull of the set of points. The α-shape of a set of points can be obtained from the Delaunay Triangulation of the set of points. For a give α, we compute the boundaries for the α-shapes as the following.

1. We first compute the Delaunay Triangulation of the set of points.
2. For each Delaunay Triangle, t, we consider the following cases.
   (a) If the length of three edges of t are less than α, t is totally in one of the connected components of its α-shape. These edges cannot be on the boundary.
   (b) If the length of the three edges of t are greater than α, t is in the exterior of its α-shape. These three edges cannot be on the boundary either.
   (c) If some of the edges of t are less than α and some of them are greater than α. We consider the edges with length less than α are in the interior of the shape. Thus the edges having length greater than α are on the boundary.

There are many factors to be considered in selection of an α value. If α is large, several contours in the image will be connected. If α is small, we could get broken contours. Generally speaking, we cannot find an α that works well for all the images.

We solved this problem using a two-step α-shape technique. For a given set of points, we first compute its α-shape using a smaller α. We then remove the points on the connected components in the α-shape that contains small number of points. Finally, we compute the α-shape of the rest of points with a larger α. Smaller α could produce many connected components. For those smaller size components generally consist of noises points. We thus keep the boundary points by removing these noise points. We then use a larger α to construct the α-shape of these boundary points to prevent broken edges. The α-shape obtained by the proposed method is either a closed contour or a planar graph. For the first case, the closed contour could be an approximation for a heart chamber. For the second case, since each face can be an approximation of a heart chamber, we compute all the faces of the planar graph. Note that, each face is a closed contour.

As mentioned previously, we need a point in the interior of the left ventricle. The closed contour that encloses the point approximates the left ventricle. There are cases that more than one closed contours can enclose the point. In this case, we approximate the left ventricle using the smallest closed contour. Since the proposed approximation is smaller than the actual heart chamber, we revised the contour using snake model technique[4].

Snake model is an energy-minimizing spline influenced by the internal energy and the image force (external energy). Internal energy makes the spline smoother. Image force pulls the spine to the salient boundary. The position of the snake is presented as $v(s) = (x(s), y(s))$, and the energy function is

$$E_{\text{snake}} = \int_0^1 E_{\text{snake}}(v(s))ds = \int_0^1 E_{\text{int}}(v(s)) + E_{\text{image(v(s))}}ds, \tag{4}$$

where E_{int} represents the internal energy of the spline due to bending and E_{image} gives rise to the image forces.

The internal energy is composed of the first order term and the second order term. The first order term makes the snake acting like a membrane. The second order term makes it like a thin plate. Internal energy function can be written as

$$E_{\text{int}} = \frac{(\alpha(s))|v_s(s)|^2 + \beta(s)|v_{ss}(s)|^2}{2} \tag{5}$$

Adjusting the weights of α and β controls the relative important image force exists for the spline corresponds to the image features like boundary. Since snake model is to minimize a function, the image force energy should be smaller when it closes to the boundary. It can be presented as

$$E_{\text{image}} = -|\Delta I(x, y)|^2. \tag{6}$$

Then the snake is attracted to the contour with large image gradients but still constraints by internal energy. Snake model needs an initial spline which is located somewhere near the boundary. The initial spline is given from the contour obtained form the two-step α-shape technique.

2.3. COMPUTE THE MITRAL ANNULAR LINE

This step is required when the mitral valve totally open. In order to separate the left ventricle and the left atrium, we have to determine the line segment connecting the base points of the mitral valves. Since we are looking for the mitral annulus that generally has higher echogenecity, we use a two-means algorithm to identify such points. Pair of such points determines a candidate mitral annular line. To calculate the sequence of mitral annular lines is modeled as a problem that finds the shortest path in a graph. The graph is a weighted graph $G(V, E)$. The set of vertices in V represent the set of candidate mitral annular lines. Each edge in E connects a pair of vertices. The weight associated with the edge represents the similarity between the pair of mitral annular lines. The weight is calculated using the optical flow technique. Finding the shortest path in G obtained a sequence of mitral annular lines. We describe the details in the following.

Since we know that the mitral annular points are on the demarcation of fat and muscle. Fat and muscle generally have higher echogenecities. We use a 2-Means algorithm to identify such points. Let the set of such points be denoted

V, and O be a point in the interior of the left ventricle and above the mitral annular points. A vertical line passing through O divides V into two sets denoted L and R respectively. A point in L and a point in R form the mitral annular line. Let p and q be the pair of points. The velocity of p and q can be estimated using the optical flow technique.

Optical flow is a technique to match the point between pairs of consecutive images. If we take the time between two images as a unit, then optical flow is used to estimate the velocity. Assume that the image brightness is stationary with respect to time. For a point p in the original image, the optical flow technique is used to determined the corresponding point p' in the next image as the following. We first set up a $(2n+1)$ by $(2n+1)$ window W_p around the point p and a $(2N+1)$ by $(2N+1)$ window W_s as the search area of p. W_s must cover the location of p'. We then estimated the sum of square differences (SSD), denoted $E_c(u,v)$, for every point in W_s as the following equation,

$$E_c(u,v) = \sum_{i=-n}^{n}\sum_{j=-n}^{n}\left[I(x+i,y+j,t) - I(x+u+i,y+v+j,t+1)\right]^2, -N \leq u,v, \leq N. \quad (7)$$

Then we calculate the probability mass function

$$R_c(u,v) = e^{-kE_c(u,v)}, \quad (8)$$

where k is a constant close to zero (0.001). Having defined the probability mass function. The expected velocity $U_{cc} = (u_{cc}, v_{cc})$ is estimated as the follow,

$$u_{cc} = \frac{\sum_{u=-N}^{N}\sum_{v=-N}^{N} R_c(u,v)u}{\sum_{u=-N}^{N}\sum_{v=-N}^{N} R_c(u,v)}, \quad (9)$$

and

$$v_{cc} = \frac{\sum_{u=-N}^{N}\sum_{v=-N}^{N} R_c(u,v)v}{\sum_{u=-N}^{N}\sum_{v=-N}^{N} R_c(u,v)}. \quad (10)$$

Because the velocities of pixels closer to p are likely to have the same velocity as the pixels far away from p, we apply a weighting function, R_n, to the velocity. R_n is inversely proportional to the distance to p. The revised velocity $\overline{U} = (\overline{u}, \overline{v})$ is

$$\overline{u} = \frac{\sum_{x_j \in Wp} R_n(u_i, v_j)u_i}{\sum_{x_i \in Wp} R_n(u_i, v_i)}, \quad (11)$$

and

$$\overline{v} = \frac{\sum_{x_i \in Wp} R_n(u_i, v_j)v_i}{\sum_{x_i \in Wp} R_n(u_i, v_i)}. \quad (12)$$

The true velocity is obtained using an iterative method. The velocity of $(n+1)$st iteration is given by

$$U^{n+1} = [S_{cc}^{-1} + S_n^{-1}][S_{cc}^{-1}U_{cc} + S_n^{-1}\overline{U}^n], \quad (13)$$

where S_{cc} is the conservation error and S_n is the neighborhood error in [5]. The algorithm iterates until difference between two successive velocities is smaller than a given threshold value.

Suppose that there are r images in a set of 2D + 1D echocardiogram. For each image, we calculated the two sets of points L_i and R_i, i=1, …, r, and the mean velocities L_{v_i} and R_{v_i}. Consider an image i. A point in L_i and a point in R_i form a line that could be the mitral annular line. Let $\overline{p,q}$ among these lines be the mitral annular line. Supposes $\overline{p',q'}$ is the mitral annular lines in the next image. The vector $\overrightarrow{p,p'}$ and $\overrightarrow{q,q'}$ should be similar to L_{V_i} and R_{V_i}, i.e., the length of $\mathbf{v}$,

$$\mathbf{v} = (\overrightarrow{p,p'} - LV) + (\overrightarrow{q,q'} - RV) \quad (14)$$

should be small.

We now present the way to model the problem as a graph. Given L_{v_i} and R_{v_i}, i=1, …, n, we construct a graph $G = (V,E)$.

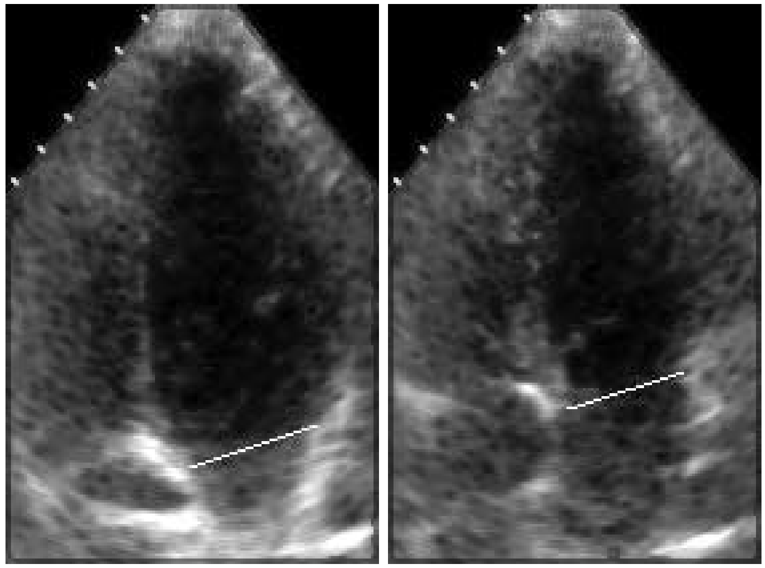

Figure 1. Two examples of the divided LV and LA

1. Let $V = \cup V_i, i = 1, \ldots, r$. Each vertex in V_i corresponds to a line connecting a point in L_i and a point in R_i, $i = 1, \ldots, r$.
2. Every vertex in V_i has a weighted edge connecting to a vertex in V_{i+1}. The weight is given as the sum of the absolute values of x component and y component of v in Eq. (14).

Having the graph G, we find the shortest path passing through vertices in V_1 to V_r. Since each vertex on the path corresponds to a line. The shortest path corresponds to the sequence of mitral annular lines in a cardiac cycle.

The 3D geometric model for left ventricle is obtained from the segmented contours obtained from the previous step. We convert these contours to contours in parallel slices. We then connect contours in consecutive slices using triangular patches.

3. EXPERIMENTS AND RESULTS

Figure 1 shows two results of the calculated mitral annular lines. A reconstructed 3D geometric model of the left ventricle is shown in Figure 2. To find out the mitral annular lines in 25 images needs 15 minutes (PIII 450 CPU). To find out the left ventricle needs 7 to 8 minutes including α-shape computing, snake model optimizing and IO times. It takes a long computing time. But the only user assist is the required of a point in the left ventricle for each plane.

4. CONCLUSIONS AND DISCUSSIONS

We present a method to reconstruct the left ventricle from precordial echocardiogram. The computation time of the proposed algorithm is long. But hte proposed approach needs very few user assists. It only needs a user input point for each plane.

There are still accuracy problem with the segmentation of the left ventricle. In the second step, the snake model cannot always accurately calculate the boundary of the heart chamber using one fixed weight for the internal energy and the external energy. It is a very difficult problem to segment the heart chamber from precordial echocardiogram.

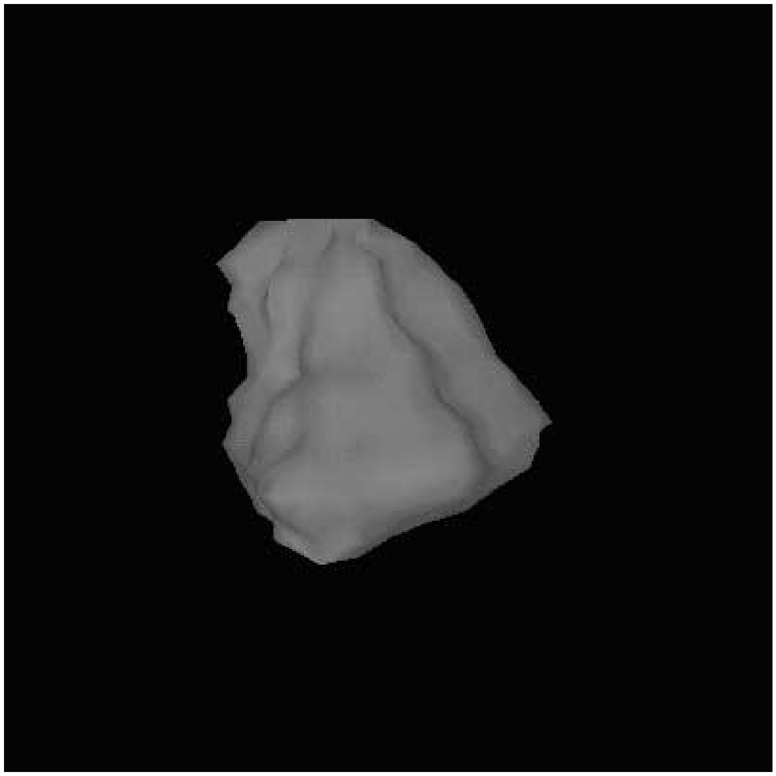

Figure 2. The reconstructed Left Ventricle

In the third step, finding the mitral annular lines, we proposed a shortest path searching approach for finding the mitral annular lines. This approach had stable performance in our experiment. However, there is a problem with the memory space consideration. Suppose there are respectively n and m points to the right and to the left of O, the number of candidates for mitral annular lines is $n \times m$. This is a large number even for small n and m. To reduce the number is a future work.

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