Two-phase Relaxation Approach for Extracting Contours from Noisy Echocardiogram Images

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Abstract:

In this work we present a technique for extracting contours from noisy echocardiogram images. In our technique, at first, an initial estimate of the boundary is obtained and then this initial contour is locally converged, in a number of steps, to the desired solution by minimising an energy function. This technique is applied to extract the contours of the heart-chambers from a sequence of echocardiogram images.

1 Introduction

One of the major objectives in medical image processing is the delineation of different objects, such as cells, different types of boundaries of various organs, cavities of ventricles and atria of heart etc. Here, we present a technique for extraction of boundaries of heart chambers from echocardiogram images. We have used active contouring [1] based relaxation technique for performing this task. A number of approaches for active contouring are available in the literature. A comprehensive survey of these techniques are given in [2].

In one of such approaches, an energy function defined over the contour snakes is minimised by solving Euler-Lagrange equation. The other class of active contouring approaches is based on the evolution of planar curves (geometric snakes) through its expansion in the direction of the normal to the curve. There is also another type of active contouring method where a path between two points is computed to obtain the global minimum in the energy model.

In our work we have considered the extraction of the closed contours only. For the nested contours, the innermost contour is extracted. We have adopted a simple heuristic to obtain a good initial estimate of the boundary. The algorithm is based on the priciple of geometric snakes and is described in section 3. In existing active contouring techniques, proper attention was not given to find a good initial estimate. In these approaches, from the users' specifications the energy minimisation process gets activated either by shrinking or by expanding the initial curves (which are usually of simple geometric shapes such as rectangles , circles etc.). That is why these techniques suffer from mainly two drawbacks. First, the contour may be locally stuck at other undesirable boundaries and secondly, the speed of the convergence is slow. It takes quite a few number of iterations to get the solution.

In processing echocardiogram images one has to take care of these two shortcomings. In some cases there are nested contours present in the echocardiogram images of the heart chambers. For example, one may observe in Figure 2(a), the presence of two closely spaced contours. The inner one is the contour of a left ventricular cavity and the outer one is the boundary of the pericardium. In our processing, our objective is to get the inner contour. Moreover, this extraction will be carried out for other subsequent frames of the echo-

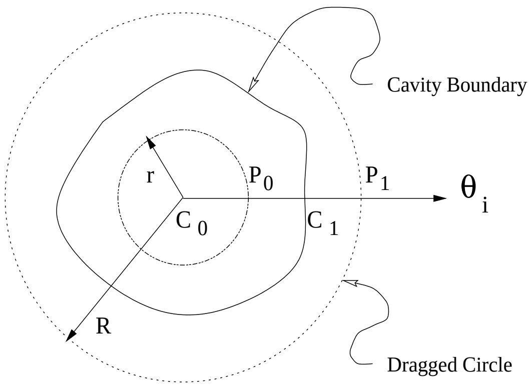


Figure 1: Initial contour point detection

cardiogram sequence and it is not possible for an user to specify the initial boundary for each and every frame. These necessitate the need for a good initial estimate computed from the users' specification in the first phase of active contouring. This computation is carried out following a ray-shooting strategy in the edge-space of the image. In the second phase we have adopted a relaxation based energy minimisation approach for finer adjustments of the contours.

2 Extraction of cavities from echocardiogram images

2.1 *Active Contour Models*

Snakes or Active Contour Models [1] are energy-minimising splines that move in the spatial domain under the influences of forces defined in the model. A traditional snake is defined as a parametric curve which dynamically changes to minimise an energy functional. The parametric description of the snake takes the following form :

$$v(s) = [x(s), y(s)],\ s \in [0, 1] \tag{1}$$

The energy associated to this snake is given by:

$$\begin{aligned} E^*_{snake} &= \int_0^1 E_{snake}(v(s))ds \\ &= \int_0^1 [E_{int}(v(s)) + E_{ext}(v(s)) \\ &\quad + E_{con}(v(s))]ds \end{aligned} \tag{2}$$

where E_{int} represents the internal energy of the curve due to bending, E_{ext} denotes the external forces, and E_{con} gives rise to the external constraint forces and $v(s)$ represents points on image space.

The internal energy of the curve can be written as,

$$E_{int} = (\alpha(s)|v^{'}(s)|^2 + \beta(s)|v^{''}(s)|^2)/2, \tag{3}$$

where $\alpha(s)$ is the measure of elasticity and $\beta(s)$ is the measure of stiffness of the spline, and both are in the range of [0,1].

The external energy is a weighted combination of the three energy functionals

$$E_{ext} = w_{line}E_{line} + w_{edge}E_{edge} + w_{term}E_{term}, \tag{4}$$

where w_{line}, w_{edge}, w_{term} are respective weights. The line energy is defined as

$$E_{line} = f(x, y) \tag{5}$$

The edge energy can be defined either as

$$E_{edge} = -|\nabla f(x, y)|^2 \tag{6}$$

or as,

$$E_{edge} = -|\nabla[G_\sigma(x, y) * I(x, y)]|^2 \tag{7}$$

where G_σ is the two dimensional Gaussian function with standard deviation σ and ∇ is the gradient operator. In our technique, to keep the values of E_{edge} as positive, we have used the following expression for the edge energy :

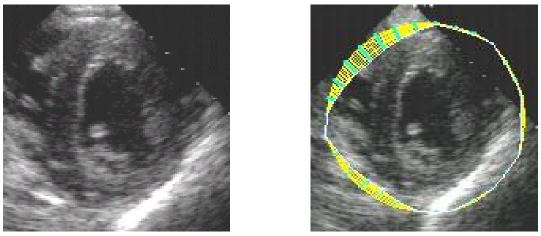
$$E_{edge} = e^{-|\nabla[G_\sigma(x,y)*I(x,y)]|^2/2\sigma^2} \tag{8}$$

One may observe that larger the edge strength, smaller the value of the edge energy.

3 Two-phase Relaxation Technique

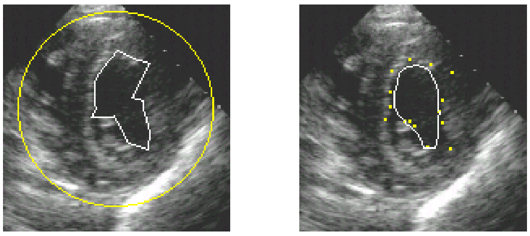
3.1 Initialisation: The First Phase

In active contouring initialisation assumes a significant role in determining the final solution. To illustrate this, let us consider the short axis view of the left ventricle of a human heart (Figure 2(a)). If the usual active contouring



(a) (b)

Figure 2: (a) original image (b) traditional snake



(a) (b)

Figure 3: (a) initial contour (b) final contour

is carried out directly from the initial specifiaction of a circle, the contour would get stuck into the outlines of the pericardium as shown in Figure 2(b). This problem due to initialisation is usually called as *capture range probelem* [3]. To overcome this drawback, we have proposed an initialisation algorithm where an user needs to provide only a circular region whose interior contains the cavity (see Figure 1). The circular region should be sufficiently large enough to enclose the chamber in both its diastolic and systolic stages. Then by scanning the edge pixels within the circular zone radially and angularly one gets the initial estimate of the contour as shown in Figure 3(a). We have used Bresenham's Line Algorithm [4] for scanning the edge space. As we found that the Canny Edge Detection Algorithm [5] performs better in the presence of noise, we have used it to get the edge description. We have further used a filtering strategy to remove the isolated and noisy edge points for determining the initial contour points along a particular direction. The algorithm is described in the following section.

3.1.1 The Algorithm

In our algorithm we have considered the detection of contour points while scanning the edge points radially and angularly about the centre of the specified circle. Let us define few notations and terminologies used in the description of our algorithm. Let us denote a circle with center at C_0 and radius R as $CRC(C_0, R)$ (see Figure 1). The sequence of points generated between two points P_0 and P_1 using Bresenham's Line Algorithm is called as a *Bresenham Sequence of points* and denoted as $BR(P_0, P_1)$. A *radial segment* of a circle $CRC(C_0, R)$ between two points P_0 and P_1 such that P_1, P_0 and C_0 are collinear is defined as the *Bresenham sequence of points* between P_0 and P_1 and it is denoted as $RS(P_0, P_1; CRC(C_0, R))$. A *full radial scan line* along the direction θ (the polar angle formed at the center C_0 (=$[x_c, y_c]$) with the x-axis) is defined as the *radial segment* $RS(C_0, p; CRC(C_0, R))$ such that

$$p = [x_c + R.cos(\theta), y_c + R.sin(\theta)]$$

. Similarly a *radial edge segment* is defined as a radial segment in the edge space of the image such that every point in the segment is an edge point and there is no other edge point in the *full radial scanline* along the same direction connected to it. We have considered *eight-connectivity* in our definition. A *radial edge segment* is *strong* if its number of elements is greater than a threshold (called as *edge strength*) , otherwise the segment is a *weak radial edge segment*. We consider an edge point is a *contour point* if it satisfies any one of the following two properties:

1. It is the last point in the sequence of a *strong radial edge segment*.

2. It is the last point in the sequence of a *weak radial edge segment*, provided the there is no edge point in ϵ number of subsequent points in the *full radial scanline* along the same direction.

It may be noted that if no point in the *full radial scan line* satifies the either of the above two properties there may not be any contour point along a direction. With these definitions and notations we are ready to present our algorithm. The sequence of contour points

Algorithm *Initial_Contour*

Input: The edge image , A Circle, $CRC(C_0, R)$ with $C_0 = [x_c, y_c]$, and maximum number of initial contour points m.

Output: Sequence of contour points: $v_0, v_1, \ldots, v_{m-1}$

Begin

1. $\theta = 0$; $i = 0$; $\Delta\theta = 2\pi/m$;

2. **for**$(\theta = 0\,;\, \theta \leq 2\,\pi\,;\, \theta = \theta + \Delta\theta)\{$

   (a) $P_0 = [x_c + r\cos\theta\,;\, y_c + r\cos\theta]$
       $P_1 = [x_c + R\cos\theta\,;\, y_c + R\cos\theta]$

   (b) **Let** $p_{\theta,0}(P_0), \ldots, p_{\theta,n-1}(P_1)$ be the sequence of points generated by Bresenham's Line Algorithm.
       for $(j = 0; j \leq n-1; j++)\{$

       if ($p_{\theta,j}$ is a *contour point*) {

       $v_i = p_{\theta,j}$;

       i=i+1;

       break;

       }

       }

   }

End *Initial_Contour*

3.2 Relaxation Technique: The Second Phase

In the second phase the initial snake (obtained from the initialisation), is moved towards the local minimum of its energy function. We have adopted a relaxation based approach to bring it down locally into the minimum energy configuration. In this method at each iteration each control point is allowed to move in one of its eight-neighbourhood points subject to the minimisation of the energy of the snake. The elastic energy and the bending energy of the control points are computed using difference approximation. Thus, with v_i corresponding to the state variable in the ith decision stage, the discrete form of the total energy E^*_{Total} can be written as,

$$E^*_{Total} = \sum_{i=0}^{m-1} E(v_i) \tag{9}$$

where

$$E(v_i) = \sum_{i=0}^{m-1} (E_{int}(v_i) + E_{ext}(v_i)) \tag{10}$$

where $E_{int}(v_i)$ is given by 3 and $E_{ext}(v_i)$ is given by the equation 4.

Since, $\forall i$, $E(v_i) \geq 0$, it is sufficient to locally minimize the energy by searching around its neighbourhood. Let $\eta(v)$ denote the eight neighborhood of the point v including the point itself. The relaxation algorithm for the energy minimisation is given below:

Algorithm *Relaxation-Contouring*

Input: Initial Contour Points $v_0, v_1, \ldots v_{m-1}$, and the gradient image.

Output: Final Contour Points $v_0, v_1, \ldots v_{m-1}$, and the gradient image.

Begin

1. $\forall i$, compute $E(v_i)$.

2. **do**{
   $\forall i$ perform the following operations:

   (a) $v_i = \mathbf{argmin}_{\forall p \in \eta(v_i)}(E(p))$

   (b) Update $E(v_i)$.

   } **while** (the change in E^*_{Total} is significant)

End *Relaxation-Contouring*

4 Results

In Figures 3(a) and 3(b) we have presented the initial and final contour obtained by the initialisation and the relaxation based energy minimisation methods respectively. To show the deviations of the initial contour points in the final result, the initial positions are marked by white dots in the Figure 3(b). In our implementation, we have kept α and β fixed for all the states with $\alpha = 0.5$ and $\beta = 0.02$. The line and edge weights were kept as $w_{line} = 2$,

$w_{edge} = 5$ respectively. In our computation, we have taken *edge strength* as 3 and ϵ for *weak radial edge segment* as 5. The standard deviation for E_{edge} calculation was taken as 10.

We have also computed the contours from a sequence of echocardiogram images from the same initial specification of the circular zone (by an user). The initial and final contours of three such subsequent frames are shown in Figures 4.

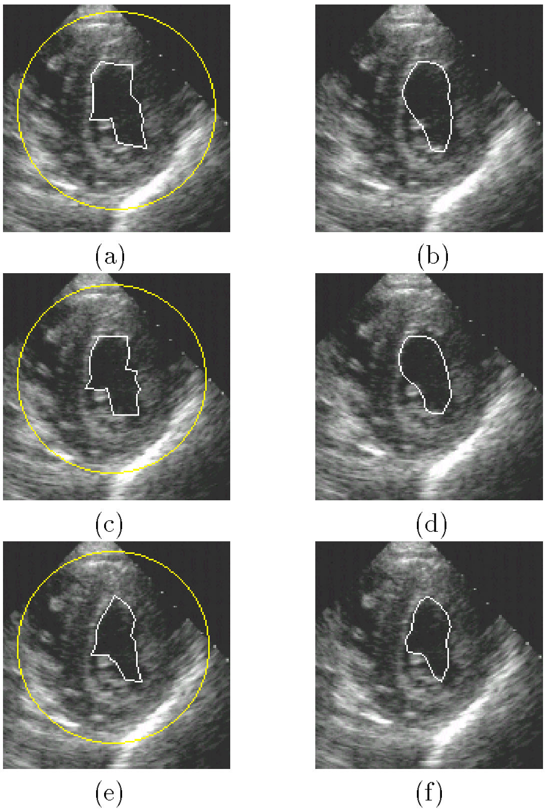


Figure 4: (a),(c),(e) initial contours, (b),(d),(f) corresponding final contours

It may be noted that we have implemented our technique on a PC with Pentium II processor and 330 MHz clock under MS Windows-95 environment. It takes around 10 iterations to converge, which is pretty fast compared to the other existing techniques [6]. To reduce the computation time, we have processed the necessary portion of the image which is the minimum bounding square of the dragged circle (by an user) on the image.

5 Conclusion

In this paper we have given a new approach to extract boundaries of cavities in echocardiogram images. In our technique, at first, an initial estimate of the boundary is obtained and then this initial contour is locally converged, in a number of steps, to the desired solution by minimizing an energy function. Our method is fast and provide reliable contours for the chambers of the hearts in echo-cardiogram sequences.

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