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Echocardiographic Image Sequence Segmentation by Multiscale Directional Snake

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Abstract—In this paper, a new algorithm named as ‘multiscale directional snake’ is proposed for segmentation of echocardiographic images by computer. The method makes use of morphological operations to locate the left ventricular center point and region of interest. In addition, a multiscale directional edge map is introduced to improve the performance of snake. The snake is confined within the region of interest during deformation and does not require initialization like traditional snake. Results show that the boundaries obtained using the proposed method fit very closely to the manually traced boundaries.

Keywords—Echocardiographic images, boundary detection, morphological operation, snake.

I. INTRODUCTION

Automatic left ventricular segmentation from echocardiographic images is an essential task for reliable and objective assessment of the heart function. However, the inherent characteristics of these ultrasound images greatly complicate this problem. Active contour model (Snake) [1] is popularly used in medical image segmentation. Chalana *et al.* has designed a multiple active contour model, which is an extension of snake to 3-D for cardiac boundary detection in echocardiographic sequences [2]. Chen *et al.* presented cell-based dual snake model [3] for ultrasound image segmentation. There is a major problem in these snake-based methods: since the snake is very sensitive to the initial position of the contour, it requires a good initialization at the beginning of deformation. In most instances, initial boundary is outlined by the user, which makes the algorithm dependent on human intervention to some extent.

In this paper, a hybrid algorithm coupling watershed segmentation and multiscale edge map for snakes is proposed to segment the left ventricle (LV) from echocardiographic image sequences. This algorithm first tracks the LV center and then detects the LV boundary.

II. LV CENTER DETECTION

The left ventricular center point (LVCP) can provide important information for LV boundary detection, thus expediting and facilitating the subsequent processing of image data. In [4], an automatic fuzzy-based method for estimating the location of the LVCP in a single echocardiographic image was proposed. However, its assumption that the LVCP is located approximately in the central part of the image is not valid in all situations.

Fig. 1. Preprocessing. (a) A composite image obtained from a sequence of echocardiographic images; (b) after adaptive neighborhood smoothing.

In this study, a novel approach to automatically locate the LVCP and the approximate LV region is presented. To segment the LV in a sequence of echocardiographic images from a cardiac cycle, it is not necessary to identify the LVCP for every frame as its position does not significantly change from frame to frame.

A. Preprocessing and Binary Image Processing

To enhance the intensity of the boundaries for LVCP tracking, a composite image (Fig. 1(a)) is constructed as follows. For each pixel, the intensities of the corresponding pixels of all the frames are compared and the maximum value is used for the composite image.

To reduce the influence of speckle noise, the composite image is further smoothed by the adaptive neighborhood smoothing method [5] and the value of threshold is obtained by Otsu’s method [6]. The smoothing process is repeated twice to ensure that the low-intensity regions are smoothed more thoroughly than the high-intensity regions (Fig. 1(b)). The resulting image is then converted to a binary image using the same threshold.

In the resulting binary image, there may be some extraneous objects and the heart chambers may connect with each other. The binary image (Fig. 2(a)) is subjected to a morphological *closing* with structuring element of a proper size to separate the overlapping chambers. By the *closing* operation, the isolated portions and peninsulas smaller than the structuring element are removed completely from the binary image.

Fig. 2. Binary image processing. (a) The binary image before morphological operations and (b) after morphological operations.

Fig. 3. (a) The Euclidean distance map; (b) watershed segmentation; (c) four cardiac chambers; (d) the LV endocardial region and the LVCP (indicated by a 'plus' sign).

B. Watershed Segmentation

The Euclidean distance transform of the resulting morphology image is computed (Fig. 3(a)). The intensity of each pixel in the image is assigned by the distance between the pixel and the nearest nonzero pixel of the binary image. To accomplish binary image segmentation, watershed immersion algorithm [7] is applied to the Euclidean distance map (Fig. 3(b)).

The binary image is then masked by multiplication with the label image. Every object in the masked binary image is labeled with different integer value for easy identification. Objects connected to the image border (ultrasound fan area) are removed from the image. Only the four objects representing the heart chambers are retained (Fig. 3(c)). The left ventricle can be selected based on anatomic knowledge. In this particular case, the object on the top-right of the image is considered as the approximate LV endocardial region, and the center of this region is considered as LVCP (Fig. 3(d)).

Fig. 4. Initialization for snake: the ROI (enclosed by the solid white line) and initial LV boundary (in dashed line).

III. LV BOUNDARY DETECTION

The LV endocardial (interior) boundary is detected based on the identified region of interest (ROI) and LVCP. In the watershed label map (Fig.3(b)), the catchment basin to which LVCP belongs is dilated to include the necessary edge information near the LV endocardial boundary and then define the ROI for subsequent processing (Fig. 4). The initial boundary of the next step of LV boundary detection is the border of LV endocardial region. The technique described below is applied only within the ROI to eliminate unnecessary computing of image data out of ROI.

A. Snake

The energy of the Snake $\Gamma(s)$ is defined as the sum of three energy terms:

$$E_{snake} = \oint_{\Gamma(s)} [\alpha |\Gamma_s|^2 + \beta |\Gamma_{ss}|^2 + E_{ext}(\Gamma(s))] ds. \quad (1)$$

where Γ_s and Γ_{ss} are the first and second derivatives with respect to s . α and β are coefficients associated with elastic energy and bending energy respectively. The elastic energy is responsible for the shrinking of the contour and the bending energy is minimum for a circle.

The choice of a proper external energy E_{ext} is one of the most difficult problems in deformable contour algorithms. The external energy is derived from the image and assumed to have small values for the features of interest. Conventionally it is defined so as to move the contour to the areas of high gradient (edge-based):

$$E_{ext}(x, y) = -\lambda |\nabla[G_\sigma * I(x, y)]|^2. \quad (2)$$

where ∇ is the gradient operator and G_σ is a 2-D Gaussian function with standard deviation σ . In ultrasound images with inherent speckle noise and artifacts, the external energy term cannot efficiently rely on the measure expressed in (2).

B. Multiscale Directional Edge Map

For the proposed approach, the external energy term E_{ext} is calculated from a multiscale directional edge map F as shown in (3), instead of simply using the gradient of the image.

$$E_{ext}(x, y) = -\lambda F(x, y)^2. \quad (3)$$

Fig. 5. (a) An original image; (b) the magnitude of gradient in ROI; (c) the multiscale directional edge map derived from (d)-(f); (d)-(f) the directional gradient of the three scales (from finer to coarser).

The edge map calculation is based on the *a priori* knowledge of the LV boundary. It is observed that the interior of the LV is relatively dark and the pixel intensities at the LV endocardial boundary are high. Thus the sharpness of the positive step edges outward from the center of the LV is a feature of endocardial boundary points. These edge points are detected using 2-D wavelet transform. Using the mother wavelet in the Mallat's algorithm [8], the horizontal first derivative G_x and vertical first derivative G_y of the echocardiographic image, are determined by applying 2-D discrete dyadic wavelet transform on the preprocessed image.

Next, the directional gradient is computed. The magnitude M_g and direction θ_g of the gradient are obtained from G_x, G_y as follows.

$$M_g(x, y) = \sqrt{G_x^2(x, y) + G_y^2(x, y)}. \quad (4)$$

$$\theta_g(x, y) = \text{angle}(G_x(x, y) - i * G_y(x, y)). \quad (5)$$

Let θ_p be the angle of any point P on the image with reference to LVCP, then the directional gradient M_d is determined using (6).

$$M_d = M_g * \cos(\theta_g - \theta_p). \quad (6)$$

For endocardial boundary, only positive intensity changes are identified along the radial lines from the LVCP. Hence, for the detection of endocardial boundary, only positive directional gradient at each scale j is of interest:

$$Inner^j(x, y) = \begin{cases} M_d^j(x, y) & \text{if } M_d^j(x, y) > 0; \\ 0 & \text{otherwise;} \end{cases} \quad (7)$$

for $j = 1, 2, 3$.

$$F = Inner^1 + Inner^2 + Inner^3. \quad (8)$$

To combine the multiscale information, the directional gradient from the three scales are added to obtain F as given

Fig. 6. Boundaries obtained from the proposed method for different frames of the heart-beating cycle.

in (8). In Fig. 5(c), it is found that strong edges are emphasized and the weak edges are preserved.

IV. RESULTS

The proposed method is implemented using programs written in MATLAB and applied to a sequence of 38 echocardiographic images (200×200 pixels). The parameters used in this experiment are set as $\alpha = 0.2, \beta = 0$ and $\lambda = 10$. The snake deforms for 30 iterations. It takes 4 seconds to identify the LVCP for the whole sequence and 2.4 seconds to detect the LV boundary in each image, on a Pentium IV 3.2GHz PC. The results of applying the snake algorithm are depicted in Fig. 6.

To quantitatively assess the performance of the proposed method, the difference between computer-detected boundaries and observer-defined boundaries is computed. The difference is measured by the radial distance from the LVCP between the two boundaries generated independently. Two indices are calculated: mean and root-mean-square (RMS) error (Fig. 7). The mean error is 1.21 ± 0.23 pixels, and the RMS error is 1.71 ± 0.38 pixels.

The mean correlation coefficient of the two boundaries is also evaluated to assess the closeness of fit of the boundaries. The coefficient is found to be 0.998. The high correlation indicates that the boundary detected using the proposed method matches very well with the actual boundary.

V. CONCLUSION

A multiscale directional snake method coupling morphological operations and the snake is proposed to automatically detect the boundary of the left ventricle from a sequence of echocardiographic images.

Fig. 7. Mean and RMS error of the computer-detected boundaries.

Compared with the traditional snake method, the proposed method does not require human intervention. The location of the LV (ROI) is identified automatically and an initial contour is generated for snake deformation. The localization of ROI reduces the interference from outer artifacts. The proposed multiscale directional edge map effectively eliminates the influence of speckle noise and yields boundaries that fit very closely to the manually traced boundaries.

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