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Watershed-Presegmented Snake for Boundary Detection and Tracking of Left Ventricle in Echocardiographic Images

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Abstract—In this paper, an automated method of boundary detection of the left ventricle (LV) is proposed. The method uses a watershed transform and morphological operation to locate the region containing the LV, then performs snake deformation with a multiscale directional edge map for the detection of the endocardial boundary of the LV.

Index Terms—Boundary detection, echocardiographic images, morphological operation, snake.

I. INTRODUCTION

Two-dimensional (2-D) echocardiography is a valuable diagnostic imaging modality for patients with heart diseases. With increasing computational power, automatic detection of the left ventricle (LV), and particularly the endocardial boundary from echocardiographic images, is a very useful step for clinical diagnosis.

In this paper, a novel approach to automatically locate the LV region has been developed. The proposed method also makes use of a multiscale directional edge map to improve the performance of the snake model. Park and Keller [1] presented an approach called watersnake for boundary detection, where the watershed transformation is used to reduce the complexity of the snake energy minimization process by providing candidate points for the true object boundary. In contrast, our method uses watershed to presegment the region of interest (ROI), which not only expedites boundary detection, but also generates the initial position of snake.

II. METHOD

The automatic detection of the LV endocardial boundary involves ROI segmentation and LV boundary determination.

A. ROI Segmentation

In the first phase of the automatic detection of the LV boundary, the ROI is identified. A composite image [Fig. 1(a)] is generated whose pixel intensities are set to be the maximum values of all the corresponding pixels at the same position in a sequence of images. The four heart chambers are better bounded in the composite image, and thus are easier to segment than in a single frame of image. Segmenting the ROI from the composite image provides an initial condition, thus facilitating the second phase of boundary detection. The steps involved are described as follows:

1) *Preprocessing*: To reduce the influence of speckle noise, the composite image is smoothed by the adaptive neighborhood smoothing method [2]. Since the interior region of the ventricle has intensities consistently below a threshold gray level τ , a large smoothing kernel is used for pixels below τ , and a small smoothing kernel is used for pixels above τ . For an image of $m \times n$ pixels, the sizes of the large kernel and the small kernel are $K_l \times \sqrt{m \times n}$ and $K_s \times \sqrt{m \times n}$, respectively. The smoothing step

is repeated twice to ensure that the low-intensity regions are smoothed more thoroughly than the high-intensity regions.

2) *Binary Image Processing*: The preprocessed image [Fig. 1(b)] is then converted to a binary image by the threshold τ . The binary image [Fig. 1(c)] is subjected to a morphological *close* operation of radius $C \times \sqrt{m \times n}$ to separate the overlapping chambers. At the completion of this step, four regions corresponding to the cardiac chambers are visually separated [Fig. 1(d)].

3) *Watershed Segmentation*: The Euclidean distance transform of the image after *close* is computed [Fig. 1(e)]. To accomplish binary image segmentation, the watershed immersion algorithm [3] is applied to the Euclidean distance map to produce the label image [Fig. 1(f)]. The binary image after *close* is then masked by multiplying with the label image. Every object in the masked binary image [Fig. 1(g)] is labeled with different integer value for distinct identification. In this particular case, LV is the object on the top-right of the image. In the watershed label map, the catchment basin to which this object belongs is considered as the region corresponding to the LV. This region defines the ROI, and its center is the LV center point [Fig. 1(h)].

B. LV Boundary Determination

Upon successful identification of the ROI, the second phase is to detect the LV boundary.

1) *Snake*: The LV is determined within the ROI using the snake (or active contour model). In the snake originally introduced by Kass *et al.* [4], the problem of boundary detection is formulated as an energy function minimization problem. The energy of snake $\Gamma(s)$ is defined as

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

where α and β are coefficients associated with elastic energy $|\Gamma_s|^2$ and bending energy $|\Gamma_{ss}|^2$, respectively.

The external energy E_{ext} is derived from the image and assumed to have smaller values for the features of interest. For echocardiographic images with speckle noise and artifacts which are inherent to ultrasound images, external energy for the proposed method is set to be

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

where the multiscale edge map F is applied.

2) *Edge Map Calculation*: Using a 2-D discrete dyadic wavelet transform, the horizontal derivative G_x and the vertical derivative G_y of the echocardiographic image, for the scales j ($j = 1, 2, \dots, J$), are determined by applying the wavelet transform on the preprocessed image [Fig. 1(b)]. Subsequently, the directional gradient is computed. The magnitude M_g and direction θ_g of the gradient are obtained from G_x and G_y .

The left ventricular center point (LVCP) is defined as the center of the ROI. Let θ_p be the angle of any point P in the image with reference to LVCP; then the directional gradient M_d is determined by

$$M_d^j(x, y) = M_g^j(x, y) * \cos(\theta_g^j(x, y) - \theta_p^j(x, y)). \quad (3)$$

For an endocardial boundary, only positive intensity changes are identified along the radial lines from the LVCP. Hence, for the detection of endocardial boundary, only the positive directional gradient is of interest. In the present study, the three finest scales are used to compute the edge map. To combine the multiscale information, the directional gradients from the three scales M_{endo}^j are added. In the resultant multiscale directional edge map F , strong edges are emphasized, and weak edges of coarser scales are also preserved.

3) *Snake Deformation*: After obtaining the edge map F , the snake is deformed with the external energy defined in (2) to determine the LV boundary. The border of the ROI is used as the initial curve for

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Fig. 1. ROI segmentation. (a) Composite image before preprocessing. (b) After preprocessing. (c) Binary image before morphological close. (d) After morphological close. (e) Euclidean distance map. (f) Label image. (g) Masked binary image. (h) ROI and LV center point.

Fig. 2. LV boundary detection results of Experiments I–V in end-diastole frames (first row) and end-systole frames (second row).

endocardial boundary determination. To track the LV boundary in a sequence of echocardiographic images, such as from a cardiac cycle, the detected boundary from one frame can be used as the initial curve for the next frame.

III. EXPERIMENTS AND DISCUSSION

A. Parameters

There are six parameters involved in the proposed method: the threshold τ , K_l , and K_s for smoothing kernel sizes, C for structuring element size, and the energy weights α and β . The value of τ is obtained by Otsu's method [5]. The other five parameters of the method are set as $K_l = 0.025$, $K_s = 0.0125$, $C = 0.04$, $\alpha = 0.1$, and $\beta = 0.1$ for all the experiments. The values of these parameters are determined by trial-and-error to obtain optimal results.

We give the following guidelines for adjusting the values of these parameters for other images. As indicated in Section II, the smoothing kernel sizes and structuring element size are set to be proportional to the size of the image by K_l , K_s , and C . Their optimal values are decided by the size of the object (LV) in the image. K_l , K_s , and C are constant for normal echocardiographic images. When the ratio of the object (LV) size to the whole image size is larger/smaller than the normal ratio, larger/smaller values are required for the three parameters.

B. Results

In Experiments I–V, the proposed automated method is applied to five sequences of long axis echocardiographic images. The results of LV boundary detection are given in Fig. 2. To validate the effectiveness of the proposed multiscale directional (MD) edge map, it is compared

TABLE I
BOUNDARY ERRORS OF EXPERIMENTS I–V

Methods	Error Measures	I	II	III	IV	V	Total Norm. Error
The proposed method: MD edge map	Hausdorff Error	9.83±4.73	6.78±1.57	6.37±0.90	7.56±2.24	13.91±3.21	4.05±1.88 %
	Mean Error	3.02±0.48	2.81±0.48	2.43±0.30	3.29±0.33	4.66±0.67	1.43±0.36 %
SD edge map	Hausdorff Error	12.44±2.15	8.83±1.90	8.66±2.63	9.74±2.96	17.21±4.53	5.11±1.89 %
	Mean Error	4.97±1.00	3.01±0.53	2.69±0.50	4.16±0.76	5.46±0.60	1.86±0.60 %
MND edge map	Hausdorff Error	15.75±0.78	7.76±2.19	7.55±2.52	8.51±3.06	16.72±3.59	5.43±2.05 %
	Mean Error	5.70±0.31	2.97±0.59	2.80±0.55	3.51±0.55	6.59±1.16	2.03±0.71 %

TABLE II
AREA ERRORS OF EXPERIMENTS I–V

Methods	I	II	III	IV	V	Total
MD edge map	0.877±0.029	0.736±0.037	0.810±0.029	0.876±0.019	0.783±0.046	0.833±0.063
SD edge map	0.761±0.047	0.734±0.039	0.814±0.039	0.837±0.039	0.696±0.053	0.770±0.064
MND edge map	0.724±0.048	0.736±0.042	0.808±0.042	0.864±0.032	0.672±0.116	0.759±0.087

with a single-scale directional (SD) edge map (M_{endo}^1) and multiscale nondirectional (MND) edge map ($M_g^1 + M_g^2 + M_g^3$).

1) *Boundary Error Metrics*: To compare the boundaries generated independently by computer and expert, two boundary error metrics are calculated: Hausdorff distance and the mean absolute distance [6]. The average Hausdorff error (HE) and the average mean error (ME) in pixels from each image sequence are listed in Table I. The corresponding normalized errors are computed by dividing HE and ME by the boundary length as determined in the expert-defined boundaries. The small errors of the proposed method indicate good correlation between the boundaries detected by the proposed method and those drawn by the specialist. Compared with the SD and MND, the MD results in smaller distance errors in all the cases.

To further validate the superiority of the proposed MD edge map, the two-tailed paired t-test is conducted under the null hypothesis that there is no statistically significant difference between the two normalized distance values achieved by the MD and two other edge maps (i.e., SD and MND). Because the five sequences contain a different number of frames, and some of them have an inadequate number of frames for statistical study, the total normalized errors for all 104 images are used to conduct the t-test. The hypothesis is rejected by $p < 10^{-3}$ in terms of the normalized Hausdorff distance, and by $p < 10^{-7}$ in terms of the normalized mean absolute distance.

2) *Area Error Metric*: Another standard measure is the Jaccard similarity coefficient (intersection/union) [7], which compares the areas enclosed by the boundary detected by the computer-aided methods and the boundary drawn by the expert. The value ranges from 0 (no overlap) to 1 (total overlap). The average errors for all the image datasets are listed in Table II. As seen in the table, the MD gives better results than the SD and MND in experiments I, IV, and V. On the other hand, they give comparable area errors in experiments II and III, where the image boundaries are relatively clear and easy to detect.

The total area errors for all 104 images are used to conduct the two-tailed paired t-test under the null hypothesis that there is no statistically significant difference between the Jaccard similarity coefficient values achieved by the MD and the two other edge maps, SD and MND. The hypothesis is rejected by $p < 10^{-10}$ in both cases.

IV. CONCLUSION

A novel method coupling morphological operation and the snake model to automatically detect the boundary of the left ventricle from a sequence of echocardiographic images is proposed. The proposed method does not require intervention by a medical expert. The automatic localization of ROI reduces the interference from artifacts, and also provides an initial contour for the succeeding snake deformation.

The proposed multiscale directional edge map effectively eliminates the influence of speckle noise. The quantitative results on five image sequences show that the proposed method yields boundaries that fit very well with manually traced boundaries.

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