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<td><strong>Author(s)</strong></td>
<td>Foo, Say Wei; Kirthika Mahendran</td>
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Automated Endocardial Boundary Detection using Dynamic Directional Gradient Vector Flow Snakes

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Abstract—The endocardial boundary detection of the left ventricle (LV) of the heart is a valuable diagnostic step to determine the abnormalities of the heart. In this paper, an automated method to obtain the endocardial boundary is proposed. The watershed transformation is utilized on the morphological image to localize the region contained the LV (ROI). The DDGVF field is then utilized dynamically to deform the snake into the endocardial boundary of the LV.

I. INTRODUCTION

Echocardiogram is a test that uses ultrasound waves to create the moving picture of the heart. The two dimensional (2-D) echocardiographic images obtained from this procedure are used in determining the endocardial boundary of left ventricle (LV) of the heart for one cardiac cycle, thus obtaining a quantitative interpretation of the LV contraction dynamics. Automated tracking of this endocardial boundary from the echocardiographic images is a very useful step in diagnosing the abnormality of the heart.

There are many sophisticated methods that are proposed for boundary detection from the echocardiographic images. These methods include watershed transform, wavelet transform, active contour model, active shape model, active appearance model and artificial neural network. However, these methods require some human interventions at the initial stage such as the specification of the parameters, initial seed point, initial curve for LV boundary etc.

Of the above mentioned methods, active contour model or snakes [1], a pioneering framework introduced by Kass and Terzopolous became the basis for many significant boundary segmentation techniques such as the Gradient Vector Flow (GVF) [2], its generalization (GGVF) [3], Directional GVF (DGVF) [4] and the Dynamic Directional GVF (DDGVF) [5]. The GVF was proposed to minimize the external force, thereby increasing the capture range and improving the progress of the snake towards the boundary concavities. The generalization of the GVF snake was proposed to further improve the performance of the GVF snake in long, thin boundaries. The edge information was included in DGVF to obtain the directional gradient that helped the snake in determining the boundaries where there were multiple edges with different directions. This was further enhanced by using the directional gradient information in a dynamic external field to achieve better performance. The dynamic directional gradient vector flow (DDGVF) developed in [5] was applied on short axis echocardiographic images for determining the LV boundary. Although the method discerned the edges well, it needed human interventions in specifying the initial contour and parameters.

An automatic fuzzy-based method for estimating the location of the LVCP in one echocardiographic image was proposed in [6]. The system uses descriptive features of the LVCP in the extraction process. The rationales behind this fuzzy based approach are: (1) LVCP usually appears as a dark hole surrounded by bright pixels in the image, and (2) it is located approximated in the central part of the image. However, the two assumptions may not be valid in all situations. For example, the templates for dark neighborhood of LVCP may not be suitable for echocardiographic images with low resolution, and there are situations where LVCP is not in the central part of the image.

In this paper, we propose a method for detecting the endocardial boundary that requires no human assistance in providing the initial curve or seed point for tracking. The method also increases the accuracy by reducing the influence of the speckle noise, low contrast and artifacts. The DDGVF method in this method is developed to determine the LV boundary in long axis with the initial curve obtained from a watershed presegmentation technique. The presegmentation is done to separate the region of interest (ROI) and determine the Left Ventricle Center Point (LVCP). Performance evaluation is done by comparing the results with boundaries drawn by experts and also with the results of the method proposed in [5] that uses the snake model with multiscale directional edge map for its deformation.

This paper is organized as follows. The proposed method is described in Section II. The results of the experiments are presented in Section III followed by the conclusion in Section IV.

II. PROPOSED METHOD

The identification of ROI, a region containing the whole endocardial boundary, is the first phase in the automatic detection of the LV boundary. The ROI provides an initial condition, thus expediting and facilitating the second phase of boundary detection.

A. Region of Interest Determination

From a four-chamber-view gray-scale echocardiographic image, it is observed that the interior of the four chambers are darker than the myocardial walls. This is a characteristic
feature utilized in the LV boundary detection. A composite image is generated such that the pixel intensities have maximum values compared to the corresponding pixels in the test sequence of echocardiographic images.

The composite image is smoothed by the adaptive neighborhood smoothing method [8] to reduce the influence of speckle noise. Large smoothing kernel is used for pixels less than the threshold $\tau$ and small smoothing kernel is used for pixels above as the intensities in the interior region of the ventricle is consistently below $\tau$. 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, where $K_l$ and $K_s$ are constants. The low-intensity regions are smoothed more thoroughly than the high-intensity regions by repeating the process twice.

The smoothed image is converted to binary image by setting the threshold $\tau$ for the grey level pixel values. The holes in the binary image are filled using morphological operations to remove the extraneous objects generated by speckle noise or artifacts. The binary image is subjected to a morphological close with structure element of size $C\times\sqrt{m \times n}$ to separate the overlapping chambers, where $C$ is a constant. The morphological close makes the cardiac chambers shrink to the size and shape of the structuring element. After this step, four different regions corresponding to the four cardiac chambers are visually separated.

The Euclidean distance transform is computed from the image after the close operation and the Euclidean distance map is obtained. The watershed immersion algorithm is applied to the distance map to obtain the label image and accomplish the binary image segmentation.

The label image is multiplied with the binary image after close operation to generate the masked binary image. For distinct identification, the objects in the masked binary image are labeled with different integer values. The objects connected to the boundaries are fanned out from the image. Based on anatomical knowledge, the left ventricle in this case is the object on the top right corner. The corresponding catchment basin in the watershed label image to which this object belongs is defined as the LV region (ROI) and its center is the LV center point (LVCP).

B. LV Endocardial Boundary Detection

The endocardial boundary of the LV can be identified based on the determined ROI and the LVCP. The LV is determined within the ROI using snake. According to Kass et al [1] the problem of boundary detection is formulated as an energy function minimization problem. The DDGVF snake [5] is used to determine the boundary by minimizing the following energy function of the snake $\Gamma(s)$

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

where $\alpha$ and $\beta$ 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 feature of interest. Usually the echocardiographic images are inherited with speckle noise and artifacts. According to the proposed

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Fig. 1. Determination of ROI (a) Composite image (b) Smoothed image (c) Binary image before morphological close (d) Binary image after morphological close (e) Euclidean distance map (f) Label image (g) Masked binary image (h) LV region and LVCP: Courtesy: [7]
method, the external energy is chosen to be

\[ v(x, y) = [u^+(x, y), u^-(x, y), v^+(x, y), v^-(x, y)] \]  \hspace{1cm} (2)

This is the dynamic directional gradient vector flow (DDGFVF) field denoting the four components in four directions. These components are obtained by solving the following equation

\[ v_t = \mu \nabla^2 v - (v - df)df^2, v_0 = df \]  \hspace{1cm} (3)

where \( df = [df^+_x, df^-_x, df^+_y, df^-_y] \) and

\[ df^+_x = \frac{\partial}{\partial x} f^+_x \]
\[ df^-_x = \frac{\partial}{\partial x} f^-_x \]
\[ df^+_y = \frac{\partial}{\partial y} f^+_y \]
\[ df^-_y = \frac{\partial}{\partial y} f^-_y \]
TABLE I

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Error Measure</th>
<th>DDGVF</th>
<th>Multi-scale direction (MD)</th>
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<tbody>
<tr>
<td>I</td>
<td>Hausdorff</td>
<td>13.1715 ± 4.3644</td>
<td>12.4905 ± 2.8529</td>
</tr>
<tr>
<td>I</td>
<td>Mean</td>
<td>4.9398 ± 0.7714</td>
<td>4.5628 ± 1.0368</td>
</tr>
<tr>
<td>II</td>
<td>Hausdorff</td>
<td>9.8769 ± 4.3122</td>
<td>10.7275 ± 4.0175</td>
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<tr>
<td>II</td>
<td>Mean</td>
<td>2.8626 ± 0.6035</td>
<td>3.1930 ± 0.7244</td>
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<tr>
<td>III</td>
<td>Hausdorff</td>
<td>7.3200 ± 2.7643</td>
<td>7.5148 ± 1.7587</td>
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<tr>
<td>III</td>
<td>Mean</td>
<td>2.5775 ± 0.2938</td>
<td>2.5291 ± 0.3669</td>
</tr>
<tr>
<td>IV</td>
<td>Mean</td>
<td>4.8434 ± 0.6519</td>
<td>4.6603 ± 0.8421</td>
</tr>
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TABLE II

<table>
<thead>
<tr>
<th>Methods</th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>IV</th>
</tr>
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<tbody>
<tr>
<td>DDGVF</td>
<td>0.7320 ± 0.0161</td>
<td>0.8136 ± 0.0738</td>
<td>0.8281 ± 0.0380</td>
<td>0.7738 ± 0.0385</td>
</tr>
<tr>
<td>MD</td>
<td>0.7717 ± 0.0508</td>
<td>0.7901 ± 0.0508</td>
<td>0.8230 ± 0.0403</td>
<td>0.7649 ± 0.0542</td>
</tr>
</tbody>
</table>

The proposed procedure is performed on four different sequences of long axis echocardiographic images (Experiments I - IV). The results of these images are given in Figure 2. The performance of the proposed DDGVF edge map is compared to the multi-scale directional (MD) proposed in [7] for the end diastole and the end systole frames.

Error measures: The computer generated boundaries are compared with the boundaries drawn by expert to obtain the Hausdorff error (HE) and the average mean error (ME) [10]. These errors in pixels from each image sequence are listed in Table I for both the DDGVF and the multi-scale directional edge map. Results indicate good correlation between boundaries generated by computers and the boundaries drawn by specialist.

Jaccard similarity coefficient is another standard measure, with which the effectiveness of the program can be determined. The Jaccard similarity coefficient J is formulated as $J = \frac{vol(A \cap B)}{vol(A \cup B)}$ where A denotes the region bounded by the boundary determined by the expert and B is the area enclosed by the boundary obtained from the proposed computer generated method. The value of J for a perfect overlap is 1.0, whereas for no overlap it is 0.0 [11]. The average area errors for all the four image sequences are given in Table II.

From Tables I and II, we observe that the results on the average are significantly better than the results in [7] where the boundaries of the images are relatively difficult to detect. Further, from the results we infer that the boundaries are more distinct and prominent than those obtained from the MD. We also find that the similarity coefficients are higher for the image sequences obtained from the proposed method.

IV. CONCLUSIONS

A novel approach that includes watershed transformation in automated localization of the ROI and the DDGVF

After obtaining the external energy from Eqn.3 the snake undergoes deformation to track the endocardial boundary. The snake takes the ROI border as the initial curve for boundary determination. Thereafter, the boundary detected from one image frame is used as the initial contour for the next frame.

In [7], snake has been applied to the composite image in determining the endocardial boundary. 2D dyadic wavelet transform is used to obtain the multi-scale directional (MD) gradient, where the strong edges are emphasized and the weak edges are preserved. On this MD edge map, the snake is deformed with external energy $E_{ext}(x, y) = -F(x, y)^2$ to determine the LV boundary. In contrast, the proposed method do not require any separate algorithm to determine the directional edge map, as the DDGVF algorithm itself computes the directional gradient information for the effective deformation of the snake in the vector field. Hence, the proposed method allows us to omit the computation of directional edge map using wavelet transform, thereby simplifying the algorithm and reducing its complexity. Moreover, the directional gradient information is obtained from four directions such as $x, -x, y$ and $-y$ that enable good discernment of edges.

III. EXPERIMENTS AND RESULTS

The threshold is obtained from Otsu’s method [9] and it may vary with the input image sequence. The values of the other parameters are set as follows. $K_l = 0.025, K_s = 0.0125, C = 0.04, \alpha = 0.6$ and $\beta = 0$. The values of these parameters are obtained from trial and error method and are the same for all the experiments. The smoothing kernel size and the structuring element are proportional to the size of the image by $K_l, K_s, C$. The optimum values obtained depend on the size of the object i.e., the LV region in the image.
algorithm in tracking the boundary of LV is proposed. The DDGVF snake is used in the deformation process to determine the endocardial boundary of the heart with the ROI curve as the initial contour, thereby requiring no human intervention in providing inputs such as the initial seed point or the initial curve specifications. The proposed method uses a simple algorithm to effectively trace the endocardial boundary inspite of the hindrances of speckle noise and low contrast artifacts. Results show that, on the average, the proposed method exhibit significantly better results than the MD edge map method.

REFERENCES