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Left Ventricle Segmentation in Echocardiography Using a Radial-Search-Based Image Processing Algorithm

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***Abstract*—A new left ventricle segmentation method in two-dimensional echocardiography images is proposed. Image processing techniques combined with radial search and temporal information are used to extract the left ventricle boundary. Borders from sequential images are extracted using the proposed method, and a curve illustrating the area variation within a cardiac cycle is presented. Performance evaluation is performed by comparing the borders obtained from the presented method to those manually prescribed by a medical specialist. The new sequential radial search algorithm improved the border extraction from long-axis ultrasound images, specially the ones where the mitral valve was open. Segmentation errors due to low contrast were corrected.**

***Keywords*: Image processing, Two-dimensional echocardiography, Radial search, Sequential information.**

I. Introduction

Two-dimensional echocardiography is a technique commonly used in the assessment of cardiac diseases. Semi-automatic left ventricle segmentation using bidimensional echocardiography images may be used to extract parameters related to cardiac function.

Different left ventricle border extraction methods have been proposed. Active contour model (or snakes) has been used by several groups [1-3]. Cheng *et al.* used watershed and morphological operations to locate a region of interest that contains the left ventricle, and then used snakes to extract the border from the left ventricle internal chamber. [1]. Chalana *et al.* proposed a method called multiple active contour model, which uses a variation of active contour modeling [2].

Mathematic morphology has also been used in left ventricle segmentation. Andrade *et al.* used watershed to locate the region of interest, and morphological operators to extract the contour [4]. Choy *et al.* proposed using an elevation filter, combined with the Laplacian of the Gaussian (LoG) and watershed operators [5]. Some authors [1, 4, 6] use temporal information on the pre-processing step for image enhancement, but few of them apply temporal information on the border extraction step. Choy *et al.* used information from a reference frame border to improve subsequent border extractions [5]. The authors also describe how information from neighboring frames can improve the ventricle's border extraction, based on the nature of heart's movement during a cardiac cycle.

In this work, we present a semi-automatic algorithm that extracts the left ventricle internal cavity border using classic image processing techniques combined with radial search. On the radial search step, information from sequential frames is used to select points that are candidates for the left ventricle boundary.

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II. Segmentation Method Developed

Fig. 1 shows a block diagram of the proposed method.

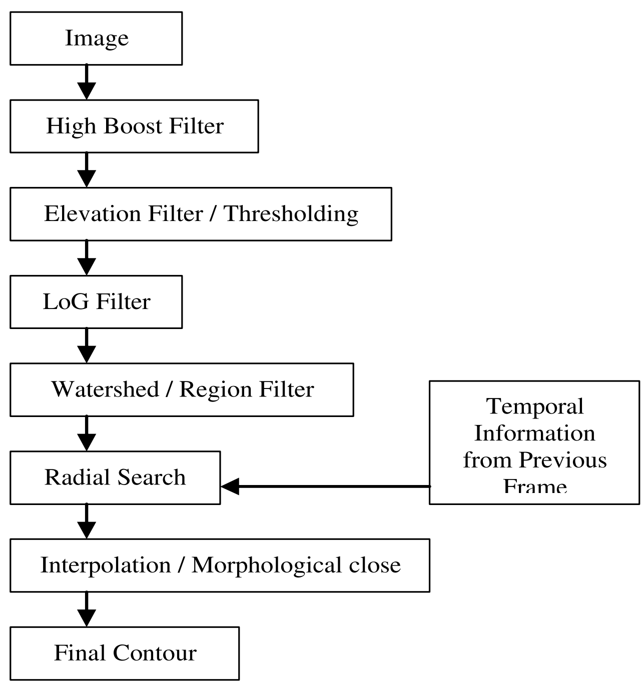

Fig. 1. Block diagram of the proposed algorithm.

A. *Pre-processing*

The first step of the pre-processing phase consists in high-boost filtering, which uses the spatial mask shown in Fig. 2.

After the high-boost filter is applied, the image typically contains a high number of minimums in the central region of the left ventricle internal cavity (Fig. 3b). Therefore, it is necessary to make this region more uniform prior to watershed segmentation, in order to avoiding super-segmentation. This is accomplished using an elevation filter and a LoG filter. First, the elevation filter [5] is applied. Then, thresholding is performed (Fig. 3c). The threshold is selected such that 65% of the pixels in the image have an intensity level lower or equal to the threshold. Finally, the LoG filter is used to identify border points from structures present in the thresheld image (Fig. 3d).

-0.1111	-0.1111	-0.1111
-0.1111	9.89	-0.1111
-0.1111	-0.1111	-0.1111

Fig 2. Mask used for the high boost filter.

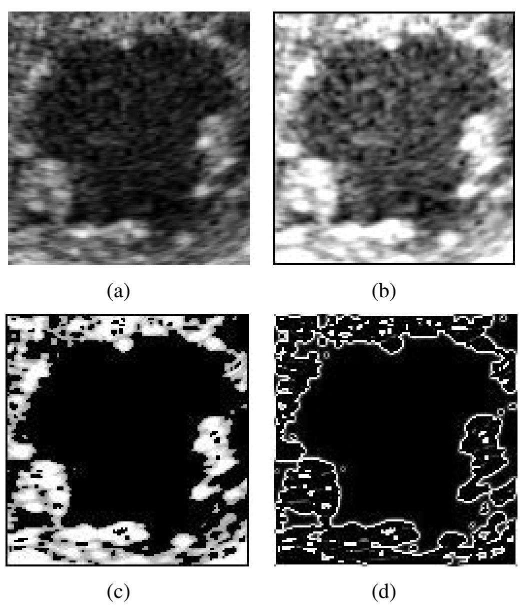

Fig. 3. Representative results from pre-processing: (a) original image, (b) after high boost filtering, (c) after elevation filtering and thresholding, and (d) after LoG filtering.

B. Boundary Extraction

In the boundary extraction step, watershed is used to identify and label regions in the pre-processed image (Fig. 4a). After region identification, a region filter is applied to eliminate small regions in the image.

The region filter scans the image, labeling and calculating the area of each region. Regions whose area is smaller then a determined threshold are merged with an adjacent region whose area is larger then the threshold. The threshold value was set to 150 pixels, and was empirically determined. This filter eliminates small regions that may occur in the left ventricle inner cavity (Fig. 4b).

The region corresponding to the left ventricle inner cavity is selected such as the inner cavity is the region whose center is the nearest to the image center, and such that the pixel that represents the center of this region is contained within the region. Using these criteria, an initial contour is obtained (Fig. 4c).

From this initial contour, the algorithm selects candidate points for the final contour. This selection is performed using radial search. Starting from the center of the initial contour, the algorithm searches for candidate points for the final contour through 360 equally spaced radii (Fig. 4d).

In order to minimize errors caused by the use of an inaccurate initial contour, only points that are distant to the countor's center by less than d pixels are considered candidate points (Fig. 4e). We used d = 100 for short-axis images and d = 180 for long-axis images.

After the selection of candidate points, shortest distance interpolation is used to transform those points into a closed contour. This interpolation is followed by morphological closing, which smoothes the the interpolated countour, and provides the final contour (Fig. 4f).

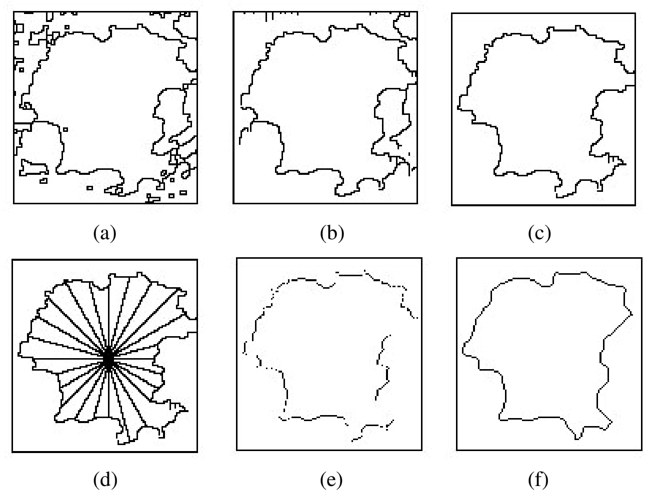

Fig. 4. Represantitve results from the boundary extraction stage: (a) the result from watershed segmentation, (b) after the region filter. (c) ventricle cavity selection, (d) radial search (24 radii), (e) candidate points after radial search, and (f) final contour of the left ventricle cavity, after interpolation and morphological contour.

This method was used for the short-axis images, and the results are shown in Table I (discussed in Section III). Next, we propose a complementary algorithm for the segmentation on long-axis images.

C. Complementary algorithm for long-axis images

One of the problems faced in bidimensional echocardiography images is low contrast and dropouts on left ventricle internal walls (Fig. 5a), which may cause segmentation errors [2, 8]. Such errors are more common when segmenting long-axis images. One way to address this issue is to use temporal information from a contour extracted from a previous frame. We propose using an extra step for segmenting long-axis image sequences, which implements a sequential radial search.

During the radial search dicussed in section II.B, a failure occurs if no candidate points are found for a particular radius (Fig. 5b). In this case, the complementary sequential algorithm is used.

The sequential algorithm searches for candidate points in the boundary extracted from a previous reference frame (Fig. 5c). These points are then considered candidate points for the current frame (Fig. 5d). This effectively corrects failures caused by low contrast and dropouts.

Fig. 5b shows a result from the isolated segmentation applied to a long-axis image in which the mitral valve is opened. Note the segmentation error near the valve, and a second failure on the right-hand side of the image, where the left ventricle wall contrast is low (arrows). Such errors may be corrected using the proposed sequential radial search algorithm (Fig. 5d).

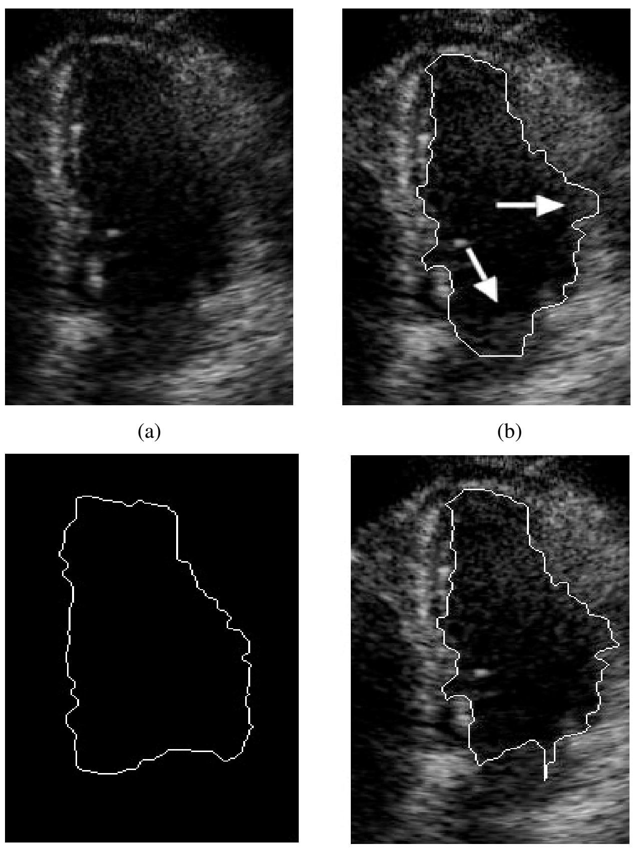

Fig. 5. Representative results from the proposed sequential radial search algorithm: (a) the original image, (b) segmentation errors in the current frame, (c) segmentation from a previous frame, used as reference, (d) the result after sequential radial segmentation.

III. RESULTS

Additional representative results are shown in Fig. 6, for both short axis and long axis images. The complementary sequential algorithm was used only with the long axis images, as we found this step unnecessary for the short axis images.

The segmentation results were evaluated for the two groups of images (short-axis and long-axis). The images from each group were classified by a medical specialist, into two subgroups: high quality and average quality. This classification was based on image contrast and border definition. The first group has 4 high quality and 7 average quality short-axis images. The second group has 7 high quality and 5 average quality long-axis images.

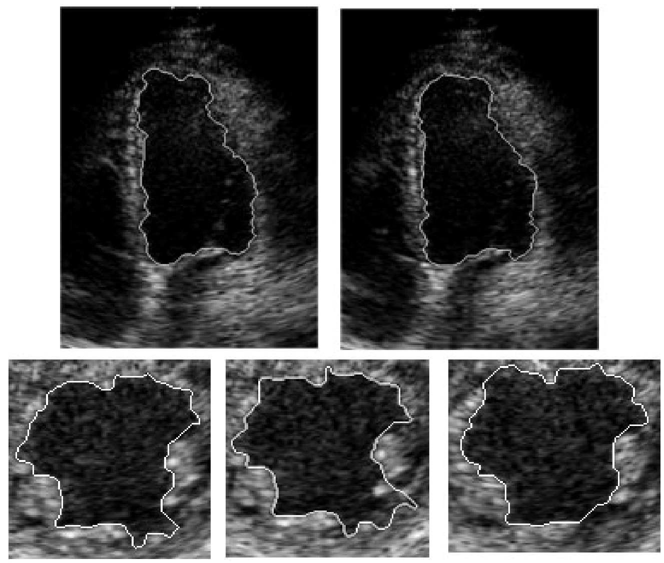

Fig. 6. Representative results obtained with the proposed methods.

The countours obtained using the proposed methods were compared to countours manually-presribed by the specialist. Three different metrics were used in this comparison: the Mean Pixel Deviation (MPD) [9], the Percentual Error (PE) [10], and the Sum Error (SE) [10]. The MPD metric makes a pixel-by-pixel comparison between the contours, while PE indicates the difference between the areas defined by manual and semi-automatic contours, and SE indicates the percentual sum of the non-overlapping areas. These three metrics are defined as follows.

$$MPD = \sum_{i=1}^{N} \frac{|M_i - A_i|}{2N} \tag{1}$$

$$PE = (|M - A| / M)x100 \tag{2}$$

$$SE = ((M - A)/M) \times 100 + ((A - M)/M) \times 100 \tag{3}$$

where M_i e A_i represents, the distance from the *i*-th point in the manual and semi-automatic contours to the manual contour's center, *M* and *A* are the inner area of the manual boundary and the semi-automatic boundary respectively, and (*M*-*A*) is the set of pixels that belong to *M*, but not to *A*.

The results obtained using these metrics are shown in Table I. For comparirson, the results obtained by Andrade *et al.* [4] are also shown.

These results show that the proposed algorithm achieved good performance. The SE and PE values for short-axis images are similar to the ones obtained by [4], and have a smaller standard deviation. This indicates that the proposed method provides better consistency.

The area variation curve for a complete cardiac cycle may be calculated by calculating the area of ventricle cavity in each frame, using the proposed algorithms (Fig 7).

TABLE I. PERFOMANCE EVALUTATION OF THE PROPOSED METHOD.

	Quality	PE	SE	MPD
Short-Axis Images	High	3.01±1.5	13.13±2.07	2.26±0.74
	Average	5.06±3.0	13.47±1.99	1.96±0.41
Long-Axis Images	High	10.65±2.47	18.51±5.06	3.27±0.73
	Average	18.06±7.49	24.62±7.89	4.56±2.82
High Quality Long-Axis Images in [4]		2.49±2.46	9.62±7.9	?

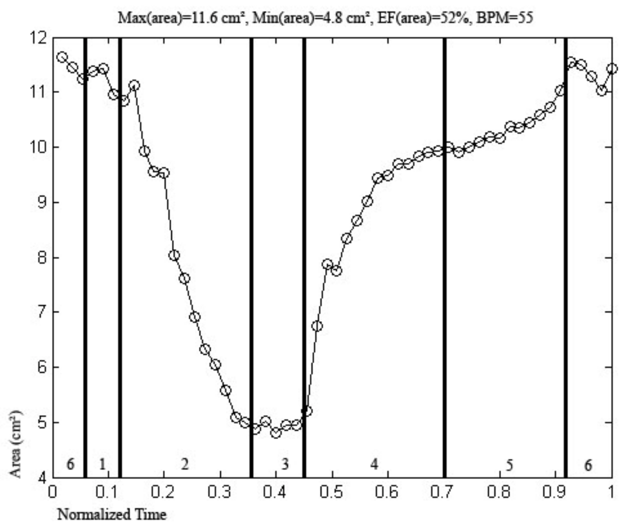

Fig. 7. Left ventricle area variation curve from short-axis image sequence representing a complete cardiac cycle. (1) isovolumetric contraction, (2) ejection, (3) isovolumetric relaxation, (4) fast filling, (5) slow filling, and (6) atrial systole.

IV. CONCLUSIONS

The proposed method uses classic image processing techniques combined with radial search to extract left ventricle boundaries in bidimensional short and long-axis echocardiography images. High boost filter and thresholding were used as a pre-processing step, which was followed by segmetntation using watershed. Then, radial search was applied to the segmentation, selecting candidate points which were then interpolated. The interpolated contour was then smoothed by morphological closing, which provided the final contour.

An approach using temporal information was also proposed: the sequential radial search. This technique reduces segmentation errors caused by low contrast and dropout in the left ventricle inner walls. The segmentation results were evaluated using three different metrics, which demonstrated that semi-automatically measured boundaries show very good agreement to those manually traced by and specialist medic.

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