

Automated Snake Initialization for the Segmentation of the Prostate in Ultrasound Images

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Abstract. Segmentation is a crucial task in medical image processing. Snakes or Active Contour Models (ACM) are valuable tools to segment images. However, they need a good initialization, which is usually provided manually by an expert. In order to achieve a reliable automation of prostate segmentation in ultrasound images, morphological techniques have been used in this work to automatically generate the initial snake. The accuracy of the proposed approach is verified by testing several images. The automated segmentation of the prostate can be done in the majority of the cases without user interaction.

Keywords: Seed Points; Initial Snake; Ultrasound; Prostate; Mathematical Morphology; Active Contour Model.

1 Introduction

Prostate cancer is a common disease for men; early detection can be helpful for effective treatment. Ultrasound imaging is a common imaging technique which is used for prostate cancer detection. On the other hand, segmentation is one of the main tasks for medical image processing. Snakes or Active Contour Models (ACM) are valuable tools to segment images [1,2] because they can guarantee smoothness and continuity of boundaries with small segmentation error [3]. However, snakes suffer from some weaknesses. For instance, they depend on the assistance of the user to initialize the snake in the vicinity of the target tissue [4, 8]. Although this assistance is sometime acceptable but it is generally an obstacle preventing a reliable and full automation of the segmentation process.

In this paper, we propose a new technique that will enable us to overcome the aforementioned drawback. By applying mathematical morphology, initial snake is generated automatically leading to a fully automated prostate segmentation. Morphological filtering and conditional erosion are used to find a portion inside the prostate. The method can be generalized to any algorithm, which needs seed

point(s) to start. By testing with 111 images, the success rate of correctly finding specific zones of prostate is 84.68%. By this achievement, the fully automated segmentation of the prostate can be achieved in the most of cases without any user interaction.

The paper is organized as follows: In section 2, a brief overview of binary mathematical morphology is given. In section 3, the proposed approach is introduced. Section 4 and 5 deliver the experimental results and the discussion. Finally, in section 6 the work is concluded.

2 Binary Mathematical Morphology(MM)

Mathematical morphology was developed based on works by Serra and Mathéron [9,10,11]. Morphology is a shape-based approach to image processing. The value of each pixel in the output image is based on a comparison of the corresponding pixels in the input image with the structuring element(SE). The MM techniques provide remarkable tools for image filtering [12], object extraction, and edge detection [13]. Dilation, erosion, opening, and closing are fundamental operators of mathematical morphology. Dilation expands the boundaries of the object; erosion, as a dual operation to dilation, shrinks the boundaries of the object. Objects and connections between them can be eliminated by opening with suitable structuring elements. Closing removes small holes on the foreground, which are smaller than the chosen SE. Combination of closing and opening is also known as morphological filtering [14].

3 Proposed Approach

The proposed approach to automated snake initialization has several steps according to the diagram in Fig. 1. The individual steps of the proposed approach are discussed in the following subsections.

3.1 Thresholding

Since the binary morphology is being used in this approach, the gray level images should be converted to a binary image. Otsu method has been applied to threshold the image [15]. This method calculates a threshold to minimize the intra-class variance of the black and white pixels in the histogram.

A test image (Fig.2.a) and its thresholded version (Fig.2.b) are shown in Fig.2. In order to have the prostate as foreground and other tissues as background in the image, the thresholded image is inverted (Fig.2.c).

3.2 Morphological Filtering

In this stage white pixels in the background and black pixels in the foreground which are smaller than selected structuring element are removed in two steps,

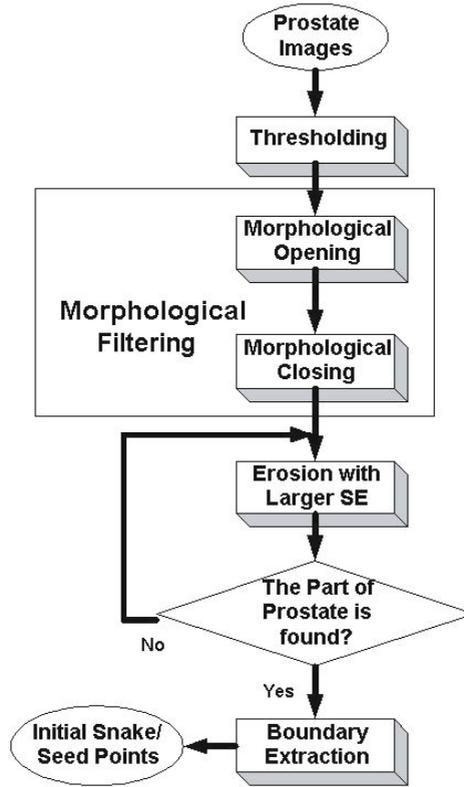


Fig. 1. The individual steps of the proposed approach

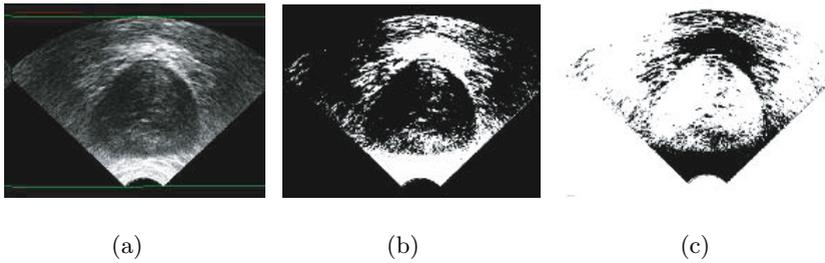


Fig. 2. Thresholding of ultrasound image by Otsu method: (a) original image, (b) thresholded by Otsu method, (c) after inversion

opening and closing. The structuring element (SE) used for filtering is defined as a disk shape with diameter of 2 pixels, as follows:

$$SE = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix}. \tag{1}$$

First, the opening step removes small islands (noisy points) and makes contours smoother. Fig.3.a shows the result of opening on the inverted binary image.

The closing step smoothes contours and removes small holes. Fig.3.b shows result of closing on opened image which is the final result of morphological filtering.

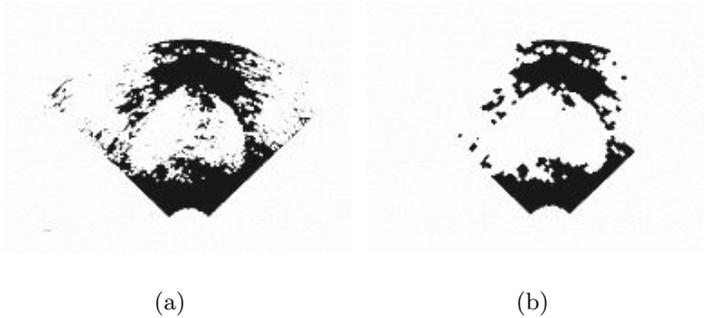


Fig. 3. Result of morphological filtering: (a) opening and (b) closing

3.3 Conditional Erosion

Erosion contracts the foreground boundary and eliminates holes on the background. Because it assigns the smallest neighborhood pixel value defined by SE to each pixel. The conditional erosion is defined by:

$$E_k = (A \ominus B_k), \quad (2)$$

where E_k is the k^{th} resulted image of erosion and B_k is the k^{th} disk shaped structuring element with diameter of $5 + 2(k - 1)$ pixels.

The condition to stop this erosion process is the remaining one object inside of the solid background. The objects are labeled and counted in each step to verify this condition.

The erosion is repeated with a two pixel larger SE in each iteration until one object remains inside of the solid background. This object, with high probability, should be a part of the prostate because the prostate obviously is the largest object in this kind of medical images. Some results for the conditional erosion are illustrated in Fig.4.

3.4 Initial Snake/Seed Points Extraction

After finding a part inside the prostate, the boundary of the detected region can be determined as follows:

$$Bound_{Int}(A) = A - (A \ominus B). \quad (3)$$

The object boundaries in the image are detected by the subtraction of the eroded image from the original image. A sample result is shown in Fig.5. This boundary, which is completely inside the prostate, can be used by active contour models as the initial snake for prostate segmentation.

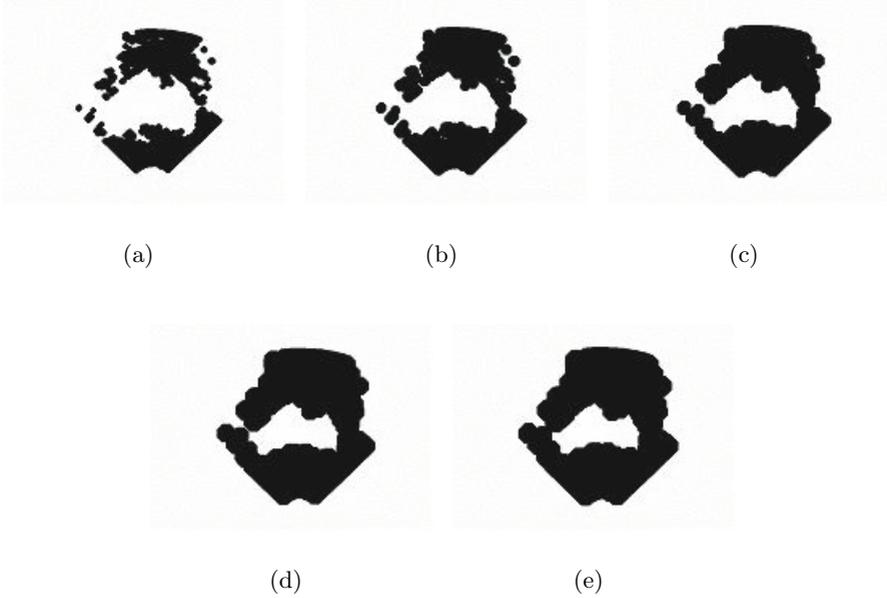


Fig. 4. Some selected results of conditional erosion: (a),(b),(c),(d) and (e) are eroded images after 1, 3, 5, 7, and 9 iterations, respectively

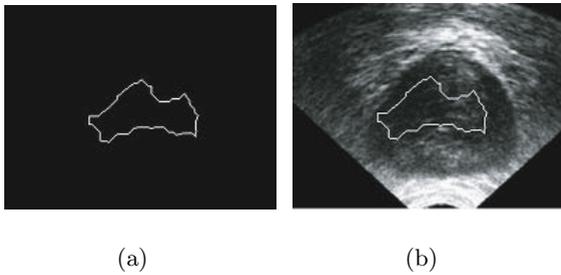


Fig. 5. (a) Initial snake resulted by applying internal boundary detection approach. (b) the resulted snake is completely inside of the prostate, and can be used as an initial snake for final prostate segmentation.

4 Experimental Results

The approach has been tested by 111 low quality prostate ultrasound images. In 94 cases, the initial snake has been found inside the prostate, In 17 cases, however, it failed to extract an inner portion of the prostate. Hence, the total success rate of the approach is 84.68%. The results of applying the proposed approach to two images to find the initial snake inside of the prostate are shown in Fig.6.

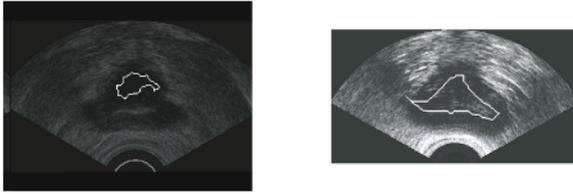


Fig. 6. The final results of applying the proposed approach to find the initial snake; as seen, the extracted initials are totally inside the prostates and ready to be used by active contour models

Failures can be categorized in two groups: 1) finding a wrong region (8 cases; 7.21%), which means the snake is not totally inside the prostate and 2) finding no region (9 cases; 8.11%); which both kind of errors are caused because of very low quality of captured images. Preprocessing prior to thresholding might decrease the failure rate.

5 Discussion

The main part of our approach after thresholding and morphological filtering, removing noise from the image foreground and background, is based on the conditional erosion. In fact we assumed that the largest object in the image is the prostate. This assumption is generally reasonable and can be supported by empirical knowledge. By applying conditional erosion we can assume that the last remaining object is (a part of) the prostate.

In the majority of the cases (84.68%) the result was what we expected but the algorithm failed also for some cases (15.32%).

Two factors caused those failed results. The first reason for failure was the existence of a shadowy region in the image, which was larger/darker/smoother than the prostate, an unusual case in this kind of images. This caused the prostate to erode earlier than the shadowy region. In fact, the shadowy region is mistaken with the prostate. An example for this case is given in Fig.7. The region enclosed by thicker line is the mentioned shadowy region. The wrong result found is marked by thinner line which is inside of that. About 47.06% of the failed cases were caused by this problem.

It seems possible to overcome this kind of problem by applying different (e.g. larger) structuring element for region outside of prostate. In fact applying adaptive structuring elements could solve this problem. Having images with higher quality could be much helpful as well.

The second reason for the failure was a complete erosion of all objects at the same time such that no specific region could be identified as the prostate. This happens when in the last step of the erosion all remaining objects are smaller than SE. About 52.94% of failing cases were caused by this phenomenon. This problem can probably be overcome by applying adaptive SE as well. For instance, one could make the SE smaller when only a small number of objects remain.

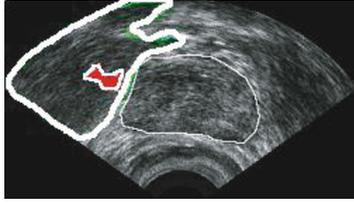


Fig. 7. An example of finding wrong result due to existence of larger adjacent shadowy region

6 Conclusion

The work in this paper aimed at automatic initialization of a snake or seed points inside the prostate in ultrasound images. The success rate of the proposed technique is 84.68% which can be improved by increasing the image quality. In fact, this work represents a possibility achieving a fully automated segmentation by snakes or active contour models. The proposed approach in this paper can eliminate user interaction to define initial snake for the segmentation of the prostate in ultrasound images.

Future objectives are directed towards adaptive thresholding and adaptive erosion. The role of thresholding in this project is essential. Conditional erosion is the main part of the method, and finding wrong result or no result has occurred in this stage. According to our experiments, it seems that we should apply the different erosion operations for the background and foreground. This means different structuring elements should be incorporated to erode the prostate region and non-prostate region differently.

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