

Contour extraction and processing in CT images

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Introduction. One of the most significant areas, in which image processing procedures are successfully used, is medical diagnostics. In this area, image processing is an important phase in order to improve the accuracy of diagnosis procedure. One of the most important phases of medical diagnostics is the pathology zone extraction from medical images, obtained by computer tomography (CT) or magnetic resonance imaging (MRI), and its further analysis. In relation to this, a task of 3D visualization of the ROI (region of interest – a biomedical object or a pathology zone) emerges in computer diagnostics. The first step is extraction of ROI contour and selection of contour control points, which are further used for 3D visualization of the object. It is important to use the methods of visualization that require a small number of control points, because of the large number of calculations necessary to visualize the object.

In this paper a method of contour extraction and selection of control points is proposed. The method extracts from the contour a minimal number of control points, which are necessary to precisely interpolate the contour.

The most difficult type of pathology zone forms is a pathology zone with boundary concavities or indentations. Existing algorithms, like active contours [1] have problems detecting such concavities, square tracing [2] deals with concavities, but results in a large number of control points. The proposed method can deal with contours of different forms and is able to select the optimal number of control points, which can then be used to visualize the pathology zone in 3D environment.

Proposed method. The proposed method consists of two parts. In the first part pathology zone is extracted from the medical image (obtained by CT). Pathology zone extraction is achieved by using a combination of thresholding, region-growing and edge-detection methods [3].

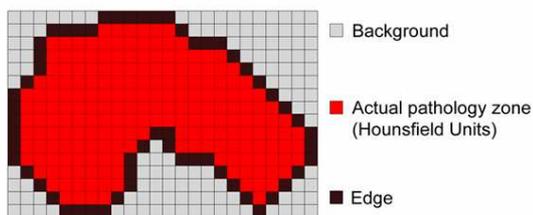


Fig. 1. Representation of the acquired two-dimensional array

Fig. 1 represents the result of the pathology zone extraction process – a 2D-array of data containing information about the segmented zone and its edge. The extracted data can then be used to obtain control points on the array.

In the second part an initial adaptive contour is selected and then corrected until it matches the original contour with some defined precision threshold T (T defines the desired distance between the adaptive contour boundary and the original contour). The second part includes the following steps:

1. Three control points are selected as the initial adaptive contour points. Boundaries are drawn between these points, forming the adaptive contour. The points of the boundaries are defined as follows:

$$y_i = y_1 - \frac{(y_2 - y_1)(x_1 - x_i)}{x_2 - x_1}, \quad (1)$$

where x_1, y_1, x_2, y_2 are the boundary starting and end points, x_i, y_i are the boundary i -th points

2. For each boundary in the adaptive contour do the following:
 - 2.1. From each point of the boundary, construct a perpendicular vector directed OUTSIDE the adaptive contour. When the vector "hits" an original contour point, calculate the distance between the boundary point and the "hit" point (2).

$$D_i = \sqrt{(x_h - x_i)^2 + (y_h - y_i)^2}, \quad (2)$$

where x_b, y_i are current boundary point, x_h, y_h are "hit" point, D_i is distance.

- 2.2. Find a boundary point (x_b, y_i) with maximum distance D_i , if $D_i > T$, then add the point (x_b, y_i) to the control points.
- 2.3. Redraw the adaptive contour.
- 2.4. Repeat 2.1-2.3 until no more points can be added to the control points.
3. For each boundary in the adaptive contour do the following:
 - 3.1. From each point of the boundary, construct a perpendicular vector directed INSIDE the adaptive contour. When the vector "hits" an original contour point, calculate the distance between the boundary point and the "hit" point (2).
 - 3.2. Find a boundary point (x_b, y_i) with maximum distance D_i , if $D_i > T$, then add the point (x_b, y_i) to the control points.
 - 3.3. Redraw the adaptive contour.
 - 3.4. Repeat 3.1-3.3 until no more points can be added to the control points.
4. Repeat steps 2-3 until no more points can be added to the control points.

Fig. 2 represents the step-by-step work of the proposed algorithm and the acquired results.

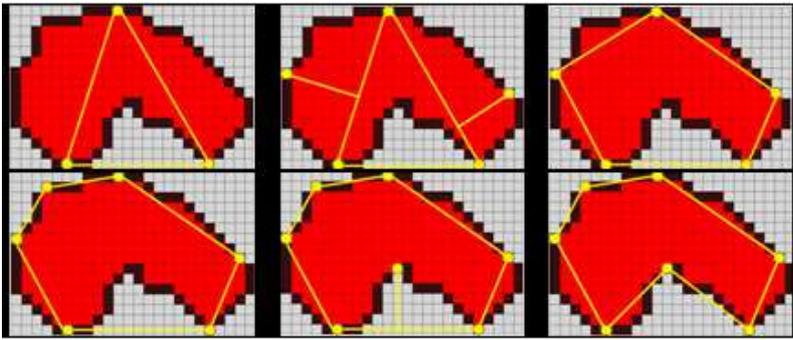


Fig. 2. Control point selection algorithm

Experiments. The proposed method was compared with square tracing algorithm, scanning algorithm, and a clockwise scanning algorithm [4] (Fig. 3).

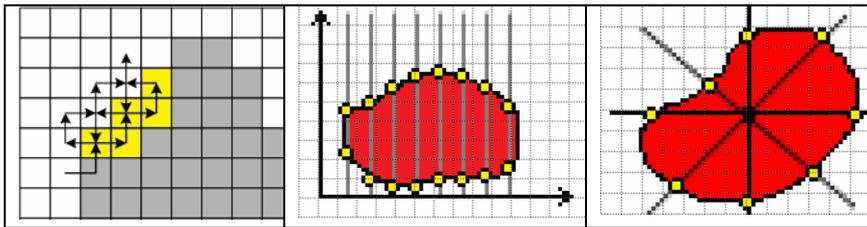


Fig. 3. Left: square tracing algorithm. Middle: scanning algorithm. Right: clockwise scanning algorithm

The experiments show that the square tracing algorithm resulted in too many control points and the clockwise scanning algorithm could not deal with boundary concavities. The scanning method was too dependent on the selected scanning step. If the step is too large, small details of the contour were skipped. If the step is too small, there were too many control points (Fig. 4).

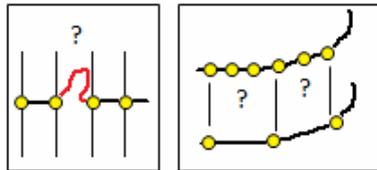


Fig. 4. Left: scanning step too large. Right: scanning step too small

The results of the proposed method are presented on Fig. 5. Different complex contours were used as a test for the proposed method, including the contours with boundary concavities. The algorithm was efficient on all types of contours.

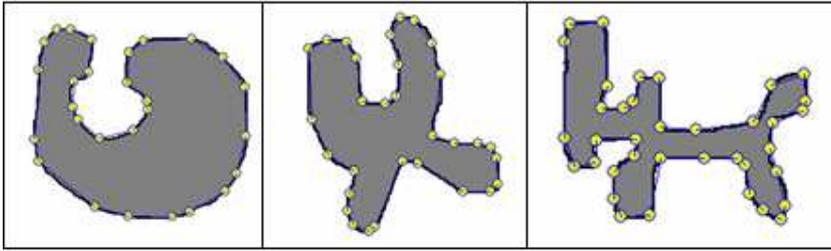


Fig. 5. Results of the proposed algorithm

Conclusions. The proposed method was more competent than the existing methods, even on complex contour forms with boundary concavities. It also proved to be an efficient approach for selecting control points for the 3D visualization, providing the minimal number of points, which were necessary to precisely interpolate the contour. The precision is measured by comparing the original contour with the adaptive contour, created from the control points. This ensures the high precision of the 3D model that can be used for further analysis, like pathology zone volume estimation.

References

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One of the most important phases of medical diagnostics is the pathology zone extraction from medical images and its further analysis. In relation to this, a task of 3D visualization of the region of interest (biomedical object or a pathology zone) emerges in computer diagnostics. It is important to use the methods of visualization that require a small number of control points, because of the large number of calculations necessary to visualize the object. In this paper a method of contour extraction and selection of control points is proposed. The method provides a minimal number of control points, which are necessary to precisely interpolate the contour. The proposed method has shown stable results even on complex contour forms with boundary concavities.