Segmentation of Ultrasound Images with Interactive B-Spline Snakes and Its Application*

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Abstract: Due to the poor quality of ultrasound images, fully automatic segmentation methods are not feasible. This article describes a novel approach to the semiautomatic segmentation of ultrasound images. Although user interaction is not required much, it is used as an important factor and incorporated into the traditional B-spline snake models. The modified model is called an interactive B snake model because the movement of the active contour is constrained through user interaction. By introducing a set of moving rules, B-spline segments are moved to the desired boundary directly. The statistical models are trained on-the-fly by observing boundaries accepted by the user. The resulting algorithm is especially useful when dealing with successive slices and provides fast, reliable and verifiable segmentation in ultrasound images. The algorithm has been used successfully on the Liver Tumor Surgical Simulation System.

Key words: B-spline snakes; segmentation; user interaction; ultrasound images; surgical simulation

Image segmentation plays an essential role in ultrasound image analyses. An accurate extraction of clinical information from ultrasound images promises reliability for clinical applications and it is the basis of 3-D model reconstruction. Due to the complex nature of ultrasound images, which mainly results from factors such as signal processing, image formation, interpolation, tissue property, interference and so on, perfect image segmentation is very difficult in practice[1] (Fig. 1). Currently, fully automatic techniques for ultrasound image segmentation are not likely to be robust. Most clinical ultrasound image systems require manual intervention. A variety of interactive segmentation methods have been developed. These methods range from totally manual drawing of object boundaries, to the detection of object boundaries with minimal user interaction.

Active contour models (commonly called snakes), were first introduced by Kass *et al.*[2], and have proved to be a powerful interactive tool for image segmentation. However, because snakes use strict local information, the implementation of the original snake model is vulnerable to its initial position and image noise. Varied approaches

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have been proposed to alleviate these problems. Cohen *et al.* introduced an internal pressure by considering the curve as a balloon which is inflated[3]. Xu *et al.* presented a new external force for active contours to solve problems associated with initialization and poor convergence to boundary concavities[4]. The snake model is also developed into a more general technique, deformable model[5].

In Fig. 1, the liver tumor boundaries in ultrasound images are not always prominent. Both segmentations satisfy the image force. Fully automatic techniques for ultrasound image segmentation are not likely to be robust. Instead we produce fast and reliable segmentations with the minimal amount of manual intervention.

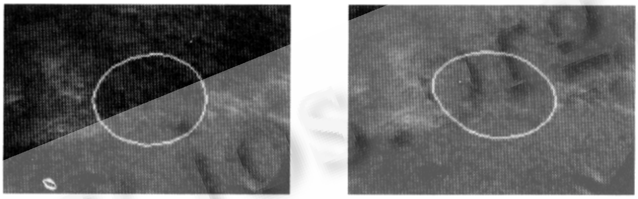


Fig. 1

All the semiautomatic image segmentation techniques require manual intervention, but manual intervention is usually used as a remediation. Especially, some ultrasound images, such as that of the liver tumor, are so complex that only experienced clinicians can recognize the boundary of the special object with the integrated knowledge of experiences, gray level and texture features. When those techniques are used in ultrasound image segmentation, manual intervention is still required a lot.

In this article, a novel semi-automatic segmentation approach of ultrasound images is presented to simulate the segmentation process of human and learn from the user interaction on-the-fly. We combine the advantages of B-spline snakes and the technique of spline-fitting for segmentation of general ultrasound images. The key ideas of the proposed snake model are to incorporate the user interaction as an important factor and train the B-spline snake model on-the-fly. We also incorporate the techniques of spline-fitting and on-the-fly statistical learning of boundary models following user interaction. Finally, we illustrate the Liver Tumor Surgical Simulation System, the application of our algorithm.

1 Interactive B-Spline Snake

A cubic B-spline is specified by $m+1$ control points $p_0, p_1, \ldots, p_m$ and comprises $m-2$ cubic polynomial curve segments. The equation of each segment is

$$r(s)=\sum_{i=0}^{m} f_i(s)p_i,\ 0\leqslant s\leqslant 1, \tag{1}$$

where f_i are the spline basis functions.

As a B-spline snake is linearly combined by a set of basic functions, and determined by the coefficients of the basic functions, compared with the piecewise linear snake models, B-spline snakes have several attractive features which make them more efficient and convenient in many applications.

1) Regularization of the shape is implicit through the fewer degrees of freedom available in the deformation, therefore the internal forces are no longer required.

2) The representation of the control points is much more compact than the long list of vertices in piecewise linear formulations.

3) The active contour composed of B-spline segments is more flexible. Through the approaches of adding and moving multiple hinges and control points, it is easy to obtain some special shapes.

4) The most useful feature for segmentation is the local control property of B-spline snakes. Modifying the position of one control point, only a small part of the curve changes. What's more, each B-spline segment may have parameters calculated locally. This feature is especially useful in local searching, and has more advantages in the images that have different properties along the boundaries.

The image force of the ultrasound image is so weak that it can't attract the snake to the idea boundary. An ordinary B-spline snake may be easily trapped by false edges and similar textures, so segmentations need user interaction.

When the snake deviates the desired boundary, the operator simply deposites a point where the boundary is lost, indicating the correct place of the desired boundary. This point is called a fixed point because the snake must be moved to cater for this restraint.

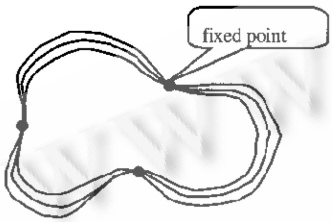


Fig. 2 An interactive B-spline snake model with three fixed points

Here, we modify the traditional B-spline snakes with the information of user interaction. The modified model was called an interactive B-spline snake because the snake's movement is constrainted by all the fixed points. Whenever the snake moves, the contour keeps passing through all the fixed points. It will still find its best place under the image force, at the same time satisfying the user's request.

For convenience, we define a control point y_i and a hinge r_i(the joining points between two spline segment) are correspondent if r_i is the head hinge of the B-spline segment decided by the control points $y_{i-1}, y_i, y_{i+1}, y_{i+2}$. A hinge's location is usually decided by three successive control points. When a hinge r_i becomes fixed, the three control points y_{i-1}, y_i, y_{i+1} should be moved under the constraint Eq. (2).

$$r_i=\frac{1}{6}(y_{i-1}+4y_i+y_{i+1}). \tag{2}$$

As the definition describes, wherever the snake changes its location, it must satisfy all the constraint equations. So when a fixed point emerges, we modify the snake model and make it pass all the fixed points which user specified. To accomplish this, we use every fixed point as a fixed hinge of the B-spline segments and every fixed hinge corresponds to one constraint equation.

Different from the traditional B-spline snake, the interactive B-spline snake need to judge the possibility of every position before calculating the location's energy during the iterative searching process. A location is possible only when it satisfies all the constraint equations, otherwise the searching process jumps to another location directly. Obviously the searching scope is smaller than before. Although additional operation of judging possible location is added into the searching process, its time is much less than the energy calculation of every location. By this way, the interactive B spline snake speeds up its searching progress.

During the process of segmentation, user can specify the place of model by minimal fixed point recursively. And the snake will adjust its location under the image force. It is a kind of compensation to weak image force, and it provides a convenient interactive tool to achieve the special forms and locations specified by the user. What's more, the interactive B-spline snakes sensibly combine the strengths of human recognition and computer algorithms. By the direction of user interaction, the interactive B-spline snake solves the problem of multiple segmentation results. This kind of semi-automatic approach is especially useful to images with poor qualities, such as ultrasound images. Under the restriction of fixed points, the snake can combine broken edges and can distinguish false edges much easier.

2 Moving Rules

If the snake's location is deviated from the desired boundary and a fixed point emerges, it is clear that several nearby B-spline segments should be moved to pass the fixed point. If we just move one or two control points to accomplish this, the local shape of the B-spline segments may be greatly changed and it will cost the snake a long time to converge to the desired boundary. Therefore when a fixed point emerges, we produce a new force field around the fixed point such that it pulls the nearby B-spline segments quickly to the desired boundary. The force field acts on not only one or two points of the B-spline segments, but also a part of or the entire contours. A control point may be inserted during the fitting process.

From the location of the fixed point, we can only estimate the direction and maximum value of the force field. On the premise of keeping previous snake's basic shapes, the objective of the force field design is to let the force act gradually on several nearest B-spline segments. The maximum force occurs at the location of the fixed point, and the force fades away as the distance grows. The function of the force field can be ignored beyond the four nearest B-spline segments. Actually the force should act directly on the points of the B-spline segments, but this will be computationally expensive. Here we propose an extremely straightforward method. We let the force field act on the control points with some approximate hypothesis. When another fixed hinge lies beside, the control point corresponding to that fixed hinge will not be moved and we use the function of leverage to extend the force field far away. When two successive hinges are both fixed, the force will be truncated here. The direction of the force to the control point corresponding to the nearest hinge is defined as along the direction of the nearest hinge to the fixed point. The directions of other conditions are simply defined as along the normal line of the corresponding hinge on the B-spline segments.

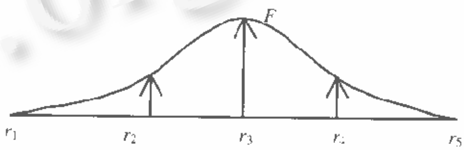


Fig. 3 From the fixed proint F, a force field is produced and wades away

According to the conditions of the two nearest hinges of point F, there are four kinds of cases. Refer to Fig. 4, r_3 is the nearest hinge to the fixed point F, and r_4 is the second nearest hinge. In general, when we move a control point, four B-spline segments change their shapes. We restrict our force field upon the control points $y_1 \ldots y_5$, so that only a part of the active contour is moved. (When the number of the control points is relatively small, maybe the entire active contour is moved.) When r_2 or r_4 is also a fixed hinge, or both, we use the leverage to extend the force field to act on the control point y_1 or y_5. An upward force on one side of the level produces a downward force on the other side.

Case 1. The two nearest hinges are both free hinges. We move the control points $y_2 \ldots y_4$ which correspond to the three nearest hinges according to the distribution of the force field, so that the nearest hinge r_3 is moved to F and becomes a fixed hinge.

Case 2. The nearest hinge is free and the second nearest hinge is fixed. We move y_2, y_3 and y_5 according to the distribution of the force field. After the movement, r_3 and r_4 are both fixed hinges.

Case 3. The nearest hinge is fixed and the second nearest hinge is free. We add a new control point $y_{3.5}$ between y_3 and y_4 and a new hinge $r_{3.5}$ emerged. We move y_2, $y_{3.5}$ and y_4. After the movement, r_3 and $r_{3.5}$ are fixed hinges.

Case 4. The two nearest hinges are both fixed hinges. We add two new control points $y_{3.3}$ and $y_{3.7}$ between y_3 and y_4 and two new hinges $r_{3.3}$ and $r_{3.6}$ emerged. We move y_2, $y_{3.3}$, $y_{3.7}$ and y_5. After the movement, r_3, $r_{3.3}$ and r_4 are fixed hinges.

On the whole, our strategy is to add a new fixed hinge and move the B-spline segments most close to the desired boundary. This location is also the "best" initial contours for the next search process. The number of control points added in each step may be varied according to the complexity of object's boundary. Multiple control points provide more flexibility and can be used to achieve special shapes.

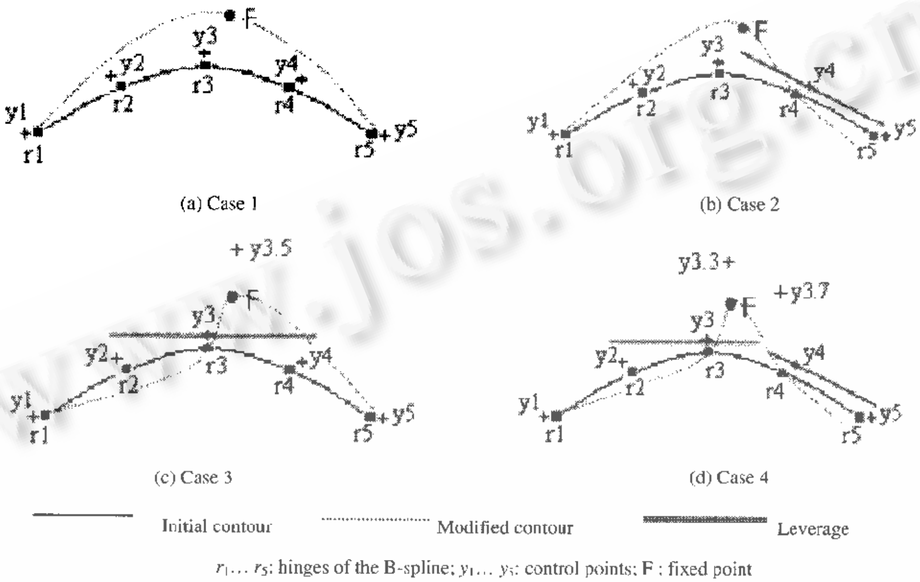


Fig. 4 The four cases

3 Image Segmentation

Image force is one of the major forces that can guide a snake to converge to the desired boundary. The difficulty in the segmentation of ultrasound images arises from the need to identify both types of edges at the same time, grey edge and texture edge. Here two potential functions based on grey edge and texture edge detection are tried respectively to guide the interactive B-spline snakes.

Conventionally, the denoising processes will be operated before implementing the image forces on snakes. However, an improper denoising may shift an edge, smear the desired edge and destroy the textures. Therefore we attempt segmentation based on the two following properties directly.

3.1 Edge detection

On the ultrasound images, a large amount of edges are very indistinct even disappeared and many false edges exist. According to this feature, we present a weighted edge detection approach.

The edge detection is exerted upon every sample point along the B-spline snake's normal lines. At every search scope, we record the maximum and minimum of the edge detection function. The location of the minimum is set as the edge point. The difference between the maximum and the minimum value is stored as the weight of the edge point. Obviously, the weight of the clear edges is much bigger than that of the indistinct edges, so that the clearer edge point has more function on the convergence of the snake. The result is that part of the clear edges can attract the entire B-spline snake to reach the ideal segmentation.

3.2 Texture detection

Usually the object of ultrasound image has different texture features along its boundary. When a fixed point exist, adjacent contour must be trapped by a minimum local value. We revise the parameters of adjacent spline segment according to the information around the fixed point.

From the current location of B-spline segment, texture statistics are gathered from both sides of the boundary and an optimal discriminator is derived between inside and outside (or equivalently, for open splines, left and right). Texture statistics information is collected from the little patches distributed beside the boundary, then the mean value and covariance matrix of the "inside" and "outside" classes are calculated respectively. Because texture statistics are usually different along an object's boundaries, every B-spline segment has its own four parameters.

When part of the contours deviates from the desired boundary and the user deposits a fixed point, we specify the inside and outside region around the fixed point by the tangent direction of the spline segment and gather samples for inside and outside region respectively. The parameters of the adjacent B-spline segments are modified by product of sample data and a distance function. In the next search process, the snakes will be more closed to the desired boundary which the user preferred. It can speed-up the convergence process and is especially useful when image properties are different along the boundaries. Such training is to magnify the local effect around the fixed point. What's more, as the boundary statistics generally change slowly from one slice to the next, such training can greatly speed-up the process of segmenting many slices through a 3D data set.

4 Liver Tumor Surgical Simulation (LTSS) System

The LTSS system provides a convenient user interaction approach. In the first slice, the user clicks on two points of the image to roughly identify the rectangle region of the interested object. Because the shape of liver tumor is usually rounded or elliptical, we use the four points of the rectangle region as the initial control points of the B-spline in the first slice. The LTSS system displays in real time the "best" contour of the interested object. If the "best" contour deviates from the desired boundary, the user simply deposits a point at the location where the boundary is lost. The process continues until acceptable contour emerges. Accurate segmentation can be achieved much quicker compared to manual delineation time. Further, the LTSS system can be trained on-the-fly to favour different types of boundaries[6].

Ultrasound-guided microwave for the treatment of liver cancer[7,8] is effective in coagulating deep tumor and protecting normal tissues. The LTSS system reconstructs the liver tumor's 3D surface model by the contours extracted from successive slices. An ellipse sphere surface model is reconstructed to simulate a water drop shape of coagulation region. We use the cutting operation between the tumor model and scalpel model to simulate the result of coagulation. What is cut out represents the coagulation region and what is left represents the tumor region. When the cutting operation is finished, surgical operation parameters are given out and the operation is evaluated by statistics. Figure 5 shows the organization graph of the LTSS system.

Figure 6 shows the segmentation process and results. In the first slice the user drops two points to roughly specify the interested region and the system searches the boundary of tumor in the region. As the boundary is not always well characterized, the B-spline snake is trapped by false edges. The user simply deposits a point where the boundary is lost. The system now refits the B-spline snake and studies from the fixed point, so that a more accurate boundary is achieved. The user continues to deposit points on the boundary until the snake achieves a satisfying result. Then the B-spline snake is propagated into the next slice and the searches are repeated. This time the snake gives an acceptable segmentation without any user interaction. Segmentation of the first slice by Sobel and Log edge operators are given out for comparison.

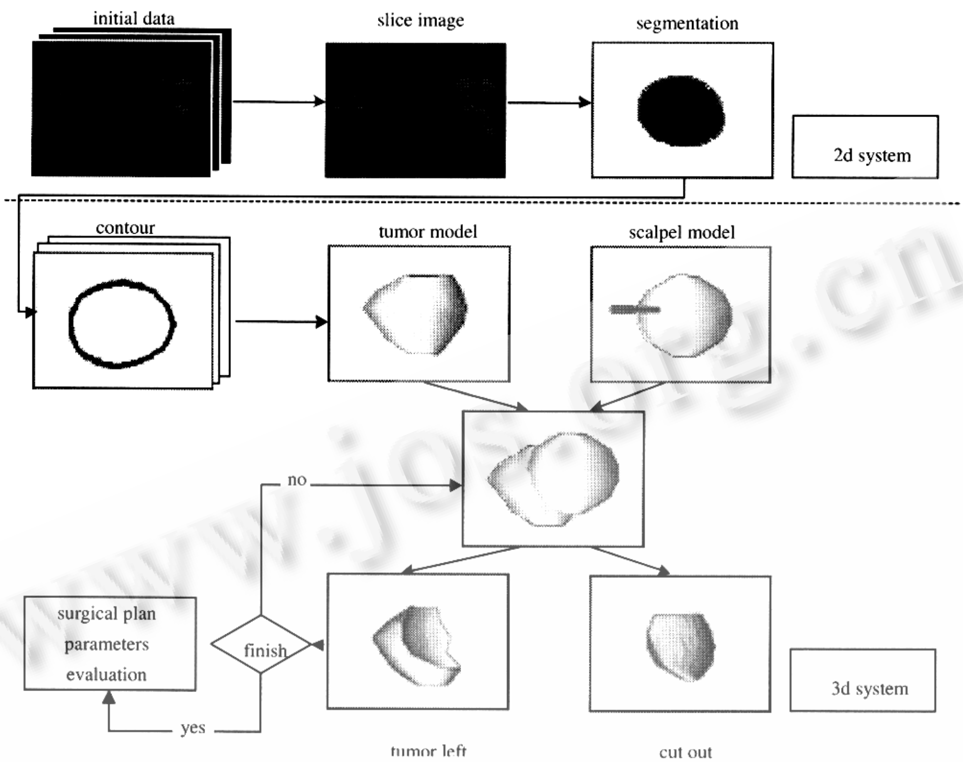
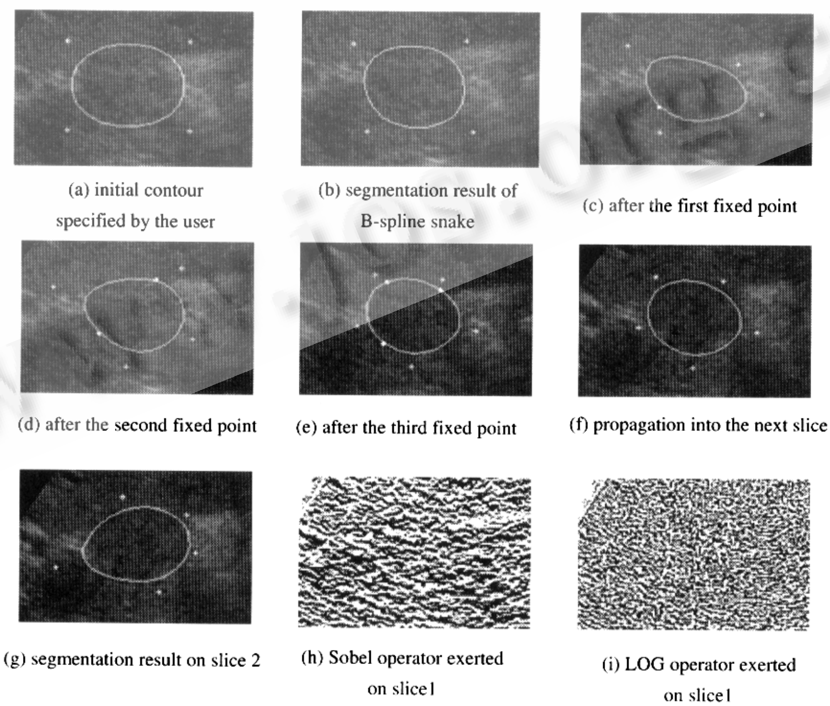


Fig. 5 Live turmor surgical simulation system



(a) initial contour specified by the user

(b) segmentation result of B-spline snake

(c) after the first fixed point

(d) after the second fixed point

(e) after the third fixed point

(f) propagation into the next slice

(g) segmentation result on slice 2

(h) Sobel operator exerted on slice1

(i) LOG operator exerted on slice1

Fig. 6 Segmentation result

The segmentation system is not computationally expensive and runs fast enough for comfortable interaction. Little user interaction is required after several first slices, because adaptive models are able to track slow changes in the boundary statistics. Even when the user interaction is required, the segmentation is usually considerably better than before.

5 Conclusions

The LTSS system has shown that the user interaction could be incorporated into the traditional B-spline snakes and exploited thoroughly to accelerate segmentations. The technique of spline fitting has been used in various ways but has rarely been applied to B-spline active contours. In this paper, we combine different techniques of active contour models, spline fitting and on-the-fly learning into a fast and reliable semi-automatic image segmentation algorithm, which have not been achieved with previous algorithms. Further work would look into exploiting prior knowledge to further improve resilience to noise, investigate other sorts of force field to describe the function of user interaction, and combine the insertion of control points with the iterative searching process of the Form Force Field into a unified scheme.

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应用 B 样条活动曲线模型实现超声图像的分割

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摘要: 超声图像由于质量较差无法实现全自动的分割方法.提出了一个新的超声图像的半自动分割方法.该方法把用户交互作为一个重要因素结合到传统的 B 样条活动曲线模型中.这种半自动的分割方法仅需少量的用户交互,

特点是:通过用户交互,规范B样条活动曲线模型,约束曲线的活动形状和范围;引入新的规则使B样条活动曲线迅速移动到用户指定的正确边界处;并且通过观察被用户接受的边界实时地训练模型.该方法是一个快速、有效的超声图像分割方法,尤其适用于连续多个相关超声图像的处理,现已成功地运用到肝肿瘤手术仿真系统当中.

关键词:B样条活动曲线模型;图像分割;用户交互;超声图像;系统仿真

中图法分类号:TP391 **文献标识码**:A