3D MEDICAL IMAGE SEGMENTATION APPROACH BASED ON MULTI-LABEL FRONT PROPAGATION

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ABSTRACT

Many practical applications in the field of medical image processing require robust and valid 3D image segmentation results. In this paper, we present a semi-automatic iterative segmentation approach for 3D medical image by combining a 2D boundary tracking algorithm and a boundary mapping process. Upon each of the consecutive slice, the boundary tracking process is accomplished in an alternate procedure of the morphological dilatation and the multi-label front propagation. The multi-label front propagation method is developed based on the minimal path theory and fast sweeping evolution method to ensure the efficiency, and speed of the boundary tracking algorithm. This 3D image segmentation approach can easily extract the close and smooth boundary of the desired object from a 2D medical image series. This approach is efficient and reliable, and requires very limited user intervention. Some experimental results are also presented to demonstrate the efficiency of this approach.

1. INTRODUCTION

Many practical applications in medical image processing field require robust and valid 3D image segmentation and visualization results for accurate analysis of anatomical structures [1]. The segmentation technique which processes the 3D voxel directly is one of the solutions, but generally it is difficulty to be implemented and very time consuming [2]. Meanwhile, it is not convenient for clinicians to extract the necessary information manually from the individual slices of medical image series.

Prior to the 3D voxel segmentation techniques, the 3D image segmentation also can be completed through a slice-by-slice process. In this situation, the segmentation process includes two steps: the boundary mapping between the connective slices and the 2D boundary tracking.

Among various 2D image segmentation and tracking techniques, active contour models have emerged as a powerful tool for semi-automatic object segmentation [1]. Its basic idea is to evolve a curve, subject to constraints from a given image, for detecting interesting objects in that image. The active contour models are often implemented based on level set method [3]. Level set method is a powerful tool to capture deforming shape. But it has the disadvantage of a heavy computation requirement even using the narrow band evolution. The fast marching method is proposed for monotonically advanced fronts [4], and is extremely faster than level set evolution. But within this method, the front only can move in monotonicity direction, it often exceed the true boundary. Generally, there are three key problems needed to be solved to implement the curve evolution methods. The first one is the initialization of the seed points. The second one is the formulation of the speed function. And the last one is the determination of the stopping criterion.

In this paper, we present a semi-automatic segmentation approach for 3D medical image by combining a 2D boundary tracking algorithm and a boundary mapping process. The boundary tracking process is accomplished in an alternate procedure including the morphological dilatation and the multi-label front propagation. The multi-label front propagation method is developed on the foundation of minimal path theory and fast sweeping evolution to ensure the efficiency, and speed of the boundary tracking algorithm. This 3D image segmentation approach solves the three key problems of curve evolution method. It is simple and fast with complexity $O(N)$, where N is the total number of grids. It can easily extract the close and smooth boundary of the desired object from a 2D medical image series. It is efficient and reliable, and requires very limited user intervention.

This paper is organized as the following. Section 2 is the details of boundary tracking algorithm. The 3D image segmentation approach is introduced in Section 3. In Sec-

This research work is financial supported by GRAVIR (Groupe Rgional d'Action pour la Valorisation Industrielle de la Recherche) of Basse-Normandie, France.

tion 4, the experimental results on the real medical image series are shown. Finally, conclusions and possible future work are discussed in Section 5.

2. BOUNDARY TRACKING ALGORITHM

The boundary tracking algorithm consists of the morphological dilatation and the multi-label front propagation. First, by using the morphological dilatation operator, the segmented boundary mapped from the previous slice is expanded to a local narrow band. Then, in the multi-label front propagation process, the inner border and the outer border of the narrow band are labeled differently, and propagate in different speed functions towards the unlabeled regions. A new boundary that separates the different labeled regions is formed within this narrow band. Through repeating the dilatation step and the multi-label front propagation step, the actual boundary of interesting object that is a global minimum within the narrow band is found.

2.1. Multi-label front propagation method

The multi-label front propagation method is developed on the foundation of minimal path theory and fast sweeping evolution. Within the minimal path theory proposed by Cohen and coauthors [5], the image is defined as an oriented graph characterized by its cost function, and the boundary segmentation problem becomes an optimal path search problem between two nodes in the graph. Minimal path theory is a global energy minimization method. It is implemented by fast marching method with complexity $O(NlogN)$ for N grid points.

Within the minimal path theory, the surface of minimal action $U(p)$ is defined as the minimal energy integrated along a path between a starting point p_0 and any point p, and is shown in Equation (1):

$$U(p) = \inf_{A_{p_0,p}} \{ \int_{\Omega} \widetilde{P}(C(s))ds \} = \inf_{A_{p_0,p}} \{E(C)\} \quad (1)$$

Where $A_{p_0,p}$ is the set of all paths between p_0 and p. $C(s)$ represents a curve on a 2D image. Ω is its domain of definition. $E(C)$ represents the energy along the curve C, and $\widetilde{P}$ is the integral potential. The minimal path between p_0 and any point p in the image can be easily deduced from the action map U by solving the following Eikonal Equation (2):

$$\|\nabla U\| = \widetilde{P} \qquad \text{with} \qquad U(p_0) = 0 \qquad (2)$$

We definite the region R_k associated with a point p_k as the set of points of the image closer in energy to p_k than to any other point. Considering all the points satisfying $U_{p_i}(p) = U_{p_j}(p)$, at these points, the front starting from p_i to computer U_{p_i} meets the front starting from p_j to computer U_{p_j} and the propagation stops. In other words, these points form the boundary between the region R_i and the region R_j.

Without loss of generality, Let X be a set of continuous points in the image, U_X is the minimal action with potential $\tilde{P}$ and starting points $\{p, p \in X\}$. Clearly, $U_X = min_{p \in X} U_p$. Considering all the point satisfying $U_{X_i}(p) = U_{X_j}(p)$, at these points, the region R_{X_i} is separated from the region R_{X_j}.

Therefore, from the above discussion, we can find a rule to extract the region's boundary by finding all the points where different minimal actions U are equal to any others. The basic idea of the multi-label front propagation method is that the independent, labeled contours propagate simultaneously with different velocities, towards the unlabeled space. The region or contour that firstly reaches the specific pixel is calculated. Whenever two (or more) contours from the same group meet, they merge into a single contour. On the other hand, if two (or more) contours from different groups meet, the contours stop evolution on the common boundaries automatically.

2.2. The front evolution scheme

Different from that in the minimal path theory, the front evolution scheme in our multi-label front propagation method is an extension of fast sweeping method because of its low complexity.

The fast sweeping method is presented by Zhao for computing the numerical solution of Eikonal equations on a rectangular grid [6]. The main idea of fast sweeping method is the combination of non-linear up-wind difference and Gauss-Seidel iterations with alternating sweeping order so that the causalities along characteristics of all directions are followed in an optimal way. The characteristics are divided into a finite number of groups according to their directions and each sweep of Gauss-Seidel iterations with a specific ordering covers a group of characteristics simultaneously. 2^n Gauss-Seidel iterations with alternating sweeping order are enough to compute a first order accurate numerical solution for the distance function in n dimensions.

The fast sweeping method has an optimal complexity of $O(N)$ for N grid points and is extremely simple to be implemented in any dimension, and gives the same result as the fast marching method. Since the low computational cost of the fast sweeping method is maintained, the complexity of our multi-label front propagation method is still $O(N)$, where N is the number of grid points.

2.3. The choice of front evolution speed

One key problem in curve evolution method is the formulation of speed function. The classical front evolution speeds rely on the edge function to stop the curve evolution. But edge features often have limited usability when there is no consistent edge strength throughout the extent of the image boundary.

Zhu and Yuille proposed a region-based segmentation method using an active contour framework [7]. They considered the region's statistical information into the evolution speed function. Another new constraint is proposed by Chan and Vese [8], in which the stopping term does not depend on the gradient of image, but is instead related to a particular segmentation of the image. Deschamps also proposed an improved fast marching method [9], in which the speed function is inversely proportional to the difference between the gray level of the starting point and other points in the image. The use of region's statistical information to differentiate the different front speeds has a bigger potential than the traditional speed function.

Furthermore, in 2D medical image series, the statistics information of the corresponding regions generally change very slowly from one slice to the next, which means that the segmented region's statistics information in one slice is a good estimate of the corresponding region in the next consecutive un-segmented slice. These information help guide the boundary tracking process. Here we introduce the region's statistical information into the speed function of the multi-label front propagation method.

First, we calculate the mean values u_{in}, u_{out} and the variances σ_{in}, σ_{out} of the region inside and the region outside the segmented boundary in the previous slice. In the boundary tracking process of the current slice, let l_{in} and l_{out} are the labels of the inner border and the outer border of the dilated narrow band from the mapped boundary. The propagation speeds for the labeled points (x, y) are decided by the following Equation (3) to Equation (5):

$$F_{in}(x,y) = \exp(\frac{|\overline{I}(x,y) - u_{in}|^2}{2\sigma_{in}^2}) + f(\nabla I(x,y)) \quad (3)$$

$$F_{out}(x,y) = \exp(\frac{|\overline{I}(x,y) - u_{out}|^2}{2\sigma_{out}^2}) + f(\nabla I(x,y)) \quad (4)$$

$$f(\nabla I(x,y)) = \frac{1}{1 + \alpha|\nabla I(x,y)|} \quad (5)$$

where $\overline{I}(x, y)$ is the average value of the image intensity in a window of size 3×3 centered at the examined point. $|\nabla I(x, y)|$ is the image local gradient, and α is a constant.

3. IMAGE SEGMENTATION APPROACH

The flowchart in Figure 1 shows the sequence of all steps we undertake for obtain the segmentation result of 3D medical image. After choose one slice in the 3D image, we segment it manually or through the fast sweeping method with the speed function proposed in reference [10]. The segmented boundary is mapped to the next slice and is used as the initial boundary of the following boundary tacking process. By repeating the dilatation process and the multi-label front propagation process alternately, the new boundary is iteratively replaced until the changes between the current boundary and that of the previous iteration is lower than the defined threshold. The segmentation on this slice is finished. And then, the boundary mapping step and the boundary tracking step are repeated until all slices in the image series are processed, and the 3D image segmentation is finished.

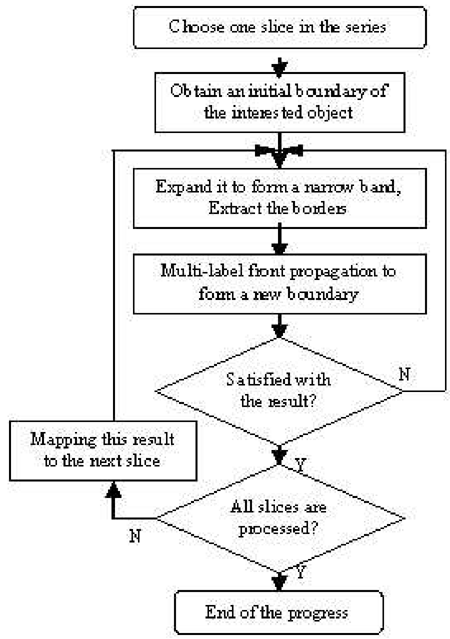


Fig. 1. Flowchart depicting the sequence of every step.

From the above discussion, we can know that this 3D image segmentation approach solves the three key problems of curve evolution method. The mapped boundary from the previous slice provides a good initialization of the boundary tracking process. In the boundary tracking process, the result of multi-label front propagation process provides the initialization for the next iteration. The speed function decided by the region's statistical information together with the gradient information ensures an appreciate evolution. The multi-label front propagation method ensures an automatic evolution stopping criterion for front propagation. The boundary tracking process stops automatically when the change between the current formed boundary and that of the previous iteration is lower than the defined threshold.

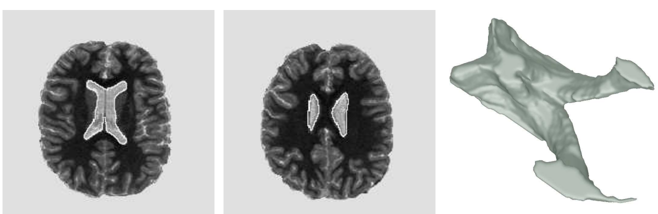
The size of the narrow band can be specified by the morphological dilatation process for a given segmentation, difference between the consecutive slices, or a class of images according to the characteristics of local minima. The reason why we use the morphological dilatation operator to obtain the narrow band is that the iteration step size can be controlled easily by adjusting the size of the structure element and the dilatation times. The structure element can be selected based on the size and shape of the object need to be segmented and the global characteristic of the processed image.

The idea of the multi-label front propagation method is similar to that in the multi-label fast marching method [11] for motion analysis in video image processing. The differences between these two approaches are the way to choose the initialize seed points and, due to the different applications, the way to classify the initialization. Furthermore, we use the fast sweeping method for the front evolution because of its lower complexity than the fast marching method.

As for the complexity of our 3D image segmentation approach, the complexity of the multi-label front propagation method is $O(N)$. The complexity of the morphological dilatation is lower than $O(N)$. The boundary tracking process can be finished in finite iterations. All the segmentation is processed on the finite slices with the number M. So the total complexity of our approach is $O(M \times N)$.

4. EXPERIMENTAL RESULTS

We test our approach on the 3D medical image. It is the MRI brain image. Figure 2(a) and (b) are the segmentation results on two different slices. Figure 2(c) is the 3D model of segmented ventricle. From the experimental results we can see that the boundary can be extracted accurately no matter the background is simple or complex.



(a) (b) (c)

Fig. 2. Segmentation result on 3D medical brain image.

5. CONCLUSIONS

In this paper, we proposed a semi-automatic approach for 3D object segmentation from a set of 2D image slices. The segmentation is completed by deforming the segmented contours from the first image towards the desired boundary in the next one, and repeating this process to the last slices. This approach is based on curve evolution and solves the three key problems of curve evolution methods. It can segment a series of medical image quickly and reliably with only little or no user intervention in each slice, and provide accurate and more robust results.

In the future, the research will be focus on how to combine with a priori information and statistical characteristics of desired objects, such as the shape, intensity profile, image modality, etc., and then improve the quality of the segmentation result.

6. REFERENCES

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