A HYBRID MEDICAL IMAGE SEGMENTATION APPROACH BASED ON DUAL-FRONT EVOLUTION MODEL

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ABSTRACT

In this paper, a hybrid medical image segmentation approach is proposed based on a dual front evolution and fast sweeping evolution. This approach is composed of two stages. In the first stage, a fast sweeping evolution with a stopping criterion based upon gradient information is adopted to give a fast and rough initial boundary estimate close to (or overlapping) the actual boundary. Next, a morphological dilation is used to expand this boundary to a narrow region large enough to contain the actual boundary. In the second stage, a dual front evolution model is used to refine the final segmentation result. In this step, the evolution speeds consider the gradient information together with less local image statistics to improve the veracity and compatibility of the algorithm. The experimental results show that this two-stage algorithm can provide close, smooth and accurate final contours with low computational complexity $O(N)$.

1. INTRODUCTION

In the computer vision literature, various methods dealing with image segmentation and feature extraction are discussed, which can be broadly grouped into edge-based techniques, region based techniques, hybrid methods, and so on [1]. Both edge-based and region-based techniques often fail to produce accurate segmentation when used alone in the segmentation of complex images. Hybrid method is a more flexible solution for achieving more accurate and consistent boundary detections.

Among the various image segmentation techniques, active contour models have emerged as a powerful tool for semi-automatic object segmentation. Snakes [2], an early implementation of active contours, use an edge-detector, which depends upon the gradient of the image, to stop the evolving curve on the boundary of the desired object. But this model has several disadvantages, such as sensitivity to initialization and difficulty of 3D extension. Many approaches have been proposed to improve the robustness and stability of snakes [3, 4, 5]. However, these active contour models still have trouble finding a good local minimum. Spurious edges generated by noise may stop the evolution of the surface, giving an undesirable local minimum of the energy.

In problems of curve evolution, the level set/fast marching methods proposed by Osher and Sethian [6, 7] have been used extensively, since they can easily handle convexities, concavities, and topological changes (splitting and merging). In these techniques, the placement of initial seed points has a major influence on the result of the final segmentation. Accordingly, Malladi et al. proposed the strategy of hybrid level set/fast marching segmentation for solving the initialization problem [8]. In this method, a small front is initialized inside the desired region, and then the fast marching evolution is used in order to greatly accelerate the initial propagation from the seed structure to the near boundary, which gives a fast and rough initialization to a costly segmentation. They used a speed function related to the image gradient information $F(x) = exp(-\alpha|\nabla(I(x))|)$. Then narrow band level set method was used to achieve the final result with the final $T(x)$ as an initial condition $\phi(x, t = 0) = T(x)$.

However, despite of all the advantages which this method can provide, the authors just consider the gradient information for the speed function to stop the curve evolution. A disadvantage of edge-based stopping functions is their inaccuracy since they depend upon a Gaussian smoothed image. In some cases, if there is a gap in the edge information, the nearest seed will flood the adjacent region. Meanwhile, the level set evolution in the second stage cannot stop automatically and ends up being very time-consuming.

In this paper, we propose a novel two-stage approach for robust and flexible medical image segmentation. It is based on a fast sweeping evolution and a dual front evolution model proposed by authors [9, 10], and is a hybrid edge and region based technique as well. The algorithm is simple and fast with complexity $O(N)$ (where N is the number of grid points in the image). Experimental results also show that this hybrid method can provide accurate, smooth segmentations within short amounts of time.

The author would like to thank Dr. Regis Clouard in GREYC-ENSICAEN, France for providing PANDORE image processing platform.

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This paper is organized as follows. Section 2 introduces the dual front evolution model. The detailed two-stage method is presented in section 3. In section 4, experimental results on a real medical image are shown. Finally, conclusions and possible extension of the algorithm are discussed in section 5.

2. DUAL FRONT EVOLUTION MODEL

In the minimal path theory proposed by Cohen and coauthors [11], the image was 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. Contrary to the classical snake model and similar to geodesic active contours [4], they presented a simplified energy model (1):

$$E(C) = \int_{\Omega} (w + P(C(s)))ds \quad (1)$$

The regularization of this model is achieved by the constant $w > 0$. The reason for modifying the energy is to have an expression in which the internal regularization energy is included in the potential term in a natural manner. The fact that the energy integral is now intrinsic will also help to explore the relation between the smoothness of the result and the potential.

Given a potential $P > 0$ that takes lower values near desired features, then looking for paths along which the integral of $\widetilde{P} = P + w$ is minimal, the surface of minimal action $U_0(p)$ is defined as the minimal energy integrated along a path between a starting point p_0 and any point p, and is shown in Eq. (2):

$$U_0(p) = \inf_{A_{p_0,p}} \{ \int_{\Omega} \widetilde{P}(C(s))ds \} = \inf_{A_{p_0,p}} \{E(C)\} \quad (2)$$

where $A_{p_0,p}$ is the set of all paths between p_0 and p. $C(s)$ represents a curve with the domain Ω of a 2D image. $E(C)$ represents the energy along the curve C, and $\widetilde{P}$ is the integral potential. $C(0) = p_0$ and $C(S) = p$. This makes the energy depend only on the geometric curve and not on its parameterization. The regularization term multiplied by the constant w, now exactly measures the length of the curve. 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 (3) (with the fast marching method for example):

$$|\nabla U| = \widetilde{P} \qquad \text{with} \qquad U(p_0) = 0 \quad (3)$$

Given the minimal action surface U_0 to p_0 and U_1 to p_1, the minimal geodesic between p_0 and p_1 is exactly the set of points p_g that satisfy the Equation (4):

$$U_0(p_g) + U_1(p_g) = \inf_{p} \{U_0(p) + U_1(p)\} \quad (4)$$

Now, let us consider all the points satisfying $U_0(p) = U_1(p)$ and the above Equation (4), at these points, the front starting from p_0 to compute U_0 first meets the front starting from p_1 to compute U_1. These points are the global minimum energy points between point p_0 and p_1. Without loss of generality, Let X be a set of continuous points in the image, U_X is the minimal action with potential $\widetilde{P}$ and starting points $\{p, p \in X\}$. Clearly, $U_X = min_{p \in X} U_p$. Considering all the points satisfying $U_{X_i}(p) = U_{X_j}(p)$ and $U_{X_i}(p_g) + U_{X_j}(p_g) = \inf_{p} \{U_{X_i}(p) + U_{X_j}(p)\}$, these points form the global minimum energy geodesic curve in the region enclosed by X_i and X_j. So, finding the minimal geodesic in a narrow region is based on finding all the points where different minimal actions U related to the separating borders of this region are equal to any others.

Then, we proposed the dual front evolution model [10]. First, suppose we have a narrow region formed by the separating inner boundary C_{in} and the outer boundary C_{out}. Without loss of generality, C_{in} and C_{out} are two sets of continuous points in the image. $U_{C_{in}}$, $U_{C_{out}}$ are the minimal action maps with potential $\widetilde{P}_{in}$, $\widetilde{P}_{out}$ and starting points $\{p, p \in C_{in}\}$, $\{p', p' \in C_{out}\}$ respectively. Considering all the points satisfying $U_{C_{in}}(p) = U_{C_{out}}(p)$ and $U_{C_{in}}(p_g) + U_{C_{out}}(p_g) = \inf_{p} \{U_{C_{in}}(p) + U_{C_{out}}(p)\}$, these points form the global minimum geodesic curve in the narrow region enclosed by C_{in} and C_{out}. By combining the dual-front evolution with some method for expending the curve to a narrow band region, the segmentation objective to find the minima with variable "degrees" globalness in the image is transferred to find the global minimum geodesic curve within a narrow band formed by the initial contour, and then iteratively replace the current contour with the obtained global minimum geodesic curve until the final segmentation objective is achieved.

The purpose of the dual front evolution model is to find the global minimum within the current narrow band. Because we can control the width of the narrow band, we can therefore control in a graceful manner just how global or local the resulting minimum will be. Sometimes the completely global minimum is just as undesirable as a minimum that is too local. The ability to control the degree of globalness is a powerful feature offered by this dual front model.

Generally, the dual front evolution can be treated as the special case of the multi-label fast marching method in [12]. Any number of independent contours propagate with different velocities depend on the label and local image characters such as mean values, variances and so on, towards the unlabeled space. The region or contour that first reaches the specific pixel is calculated, and the evolution will stop at the mutual contact point and form the new boundary automatically. The differences between these two approaches are the way to choose the initialization and the different evolution speeds, and be applied to the different applications. Furthermore, we use the fast sweeping method [13] for the front evolution because of its lower complexity than the fast marching method.

3. HYBRID SEGMENTATION ALGORITHM

The proposed hybrid algorithm includes two stages. The first stage is a local region decision. The second stage is a final boundary localization based on the dual front evolution model.

3.1. Local region decision

In this first stage, we use the fast sweeping evolution to obtain a good initial guess of the actual boundary. As for the speed function in this stage, we base it upon gradient information as proposed in [8]. Based on this definition, the speed has values very close to zero near high image gradients of the smoothed image. This helps to construct very quickly a good initial guess of the final curve.

Next, the result of this initial segmentation will be expanded to a local region zone by morphological dilation. In this way, the region size can be controlled easily by adjusting the size of structuring element and the number of dilation. It is an adaptive manner. The number of single dilation determines the size of the narrow band. The step size is also selected based on the size of the object to be segmented and the amount of noise in the data. Second, the initialized boundary is similar to the actual boundary because of the character of fast sweeping evolution, and morphological operators can preserve the coarse scale character of the initial boundary.

3.2. Final boundary localization

In this second stage, we use the dual front evolution model to achieve the final boundary. For the dual front evolution model, the inner and outer boundaries of the narrow band is already obtained from the first stage. Only the evolution speeds need to be defined.

As described above, evolution speed functions depending only upon gradient information have some disadvantages. Zhu and Yuille proposed a region-based segmentation method using an active contour framework [14]. They considered the region's statistical information into the evolution speed function. A different speed function proposed by Chan and Vese [15] yields a stopping term that does not depend on the gradient of image, but is instead related to the intensity characteristics of the image. They solve the problem as that of an energy minimization and implement it using level set methods. The same constraint is also proposed in [16, 17]. Meanwhile, we note here the inner boundary is contained in the desired object, so the mean value of this boundary should be very close to the average intensity of the desired object.

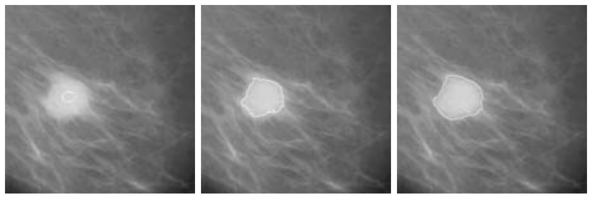
Considering all of the above reasons, we propagate the two boundaries not just according to gradient information, but together with the local mean intensity information. The propagation speed for both boundaries is:

$$F(x) = f(|I(x,y) - \mu_l|, \sigma_l^2) + g(\nabla I(x,y)) + w \quad \text{if} \quad L(x) = l \tag{5}$$

where l denotes a label, $mean(l)$ presents the mean value of all pixels with the same label l, and $g(\nabla I(x,y))$ is a function of the image gradient.

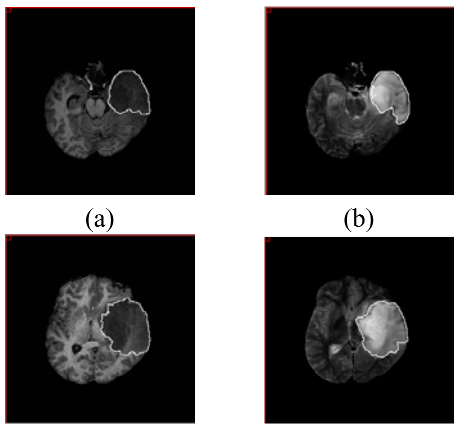
4. EXPERIMENTAL RESULTS

In this section, we test the hybrid segmentation method for the cyst image and brain tumor images. In Fig. 1, (a) is the original image with the initial curve inside the interesting object. (b) shows the segmentation result based on fast sweeping evolution, here we need to stop the evolution manually. (c) shows the final segment result based on dual front evolution, here the segmentation result in fig(b) is used as the initialization, and 5 iterations of dual-front evolution is adopted.



(a) (b) (c)

Fig. 1. The segmentation result on 2D medical image based on our two-stage method.



(a) (b) (c) (d)

Fig. 2. Segmentation result on MRI medical tumor slices.

In Fig. 2, (a) and (c) are the final segmentation results for two MRI T1-weighted tumor images, (b) and (d) are the final segmentation results for two MRI T2-weighted brain tumor images. Experimental result shows that this two-stage algorithm can achieve fast, smoothed, closed result. Generally, the same segmentation algorithm maybe applied to very different anatomical structure with different degree of success. The user should adjust some rough parameters of the algorithm for each application.

5. CONCLUSIONS

In this paper, we propose a hybrid image segmentation algorithm based on dual front evolution model. The first stage yields a coarse initial segmentation using fast sweeping evolution. The second stage refines the final segmentation by a dual front evolution model, which propagates the two different fronts with different speeds and directions, lets them mutually contact each other at the final boundary location automatically. This hybrid method is fast, accurate, and simple with computational complexity $O(N)$. Experiments show that this method can achieve smooth and accurate segmentations. One of the future research works is one 3D medical brain tumor segmentation based on dual-front evolution model.

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