IMAGE SEGMENTATION ALGORITHM

USING WATERSHED TRANSFORM AND LEVEL SET METHOD

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ABSTRACT

A novel method for image segmentation is proposed in this paper, which combines the watershed transform and region-based level set method. The watershed transform is first used to presegment the image so as to get the initial partition of it. Some useful information of the primitive regions and boundaries can be obtained. The region-based level set method is then applied for extracting the boundaries of objects on the basis of the presegmentation. The consumed time does not depend on the size of the image but the number of presegmented regions because only label level set function is updated instead of the level set function for each pixel. Therefore, the proposed method is computationally efficient. Moreover, the algorithm can localize the boundary of the regions exactly due to the edges obtained by the watersheds. The efficiency and accuracy of the algorithm is demonstrated by the experiments on the MR brain images.

Index Terms — image segmentation, watershed transform, level set method, region, MR brain image

1. INTRODUCTION

Image segmentation is one of the most difficult problems in the field of image processing and computer vision. Extracting certain structure from others is very popular nowadays especially in medical image analysis. It is very important for the diagnosis of diseases and clinical operations. Researchers have done great efforts to improve the performance of the segmentation algorithms.

Region-based level set method like C-V model is widely applied in the image segmentation [1][2] in recent years due to its ability of handling topological changes naturally. Although it has achieved good performance in the segmentation tasks, the shortcomings still limit the application of level set method. For example, it is sensitive to the initial placement of the contour. If the initial contour contains the part which belongs to the unwanted area, the model may perform poorly. It is still time-consuming. Narrow band [3] and fast marching algorithm [4] have been presented for many years but the implementation problems still exist such as the choice of the narrow band and the velocity function. Shi et. al. [5] proposed an algorithm which does not need to solve the partial differential equation and speeds up the implementation of the method. But it does not strictly converge to the weak edges and concave boundaries.

In this paper we propose a novel approach for fast extracting the boundaries of the object exactly. The basic idea includes two procedures: The primitive region information of the images is obtained by using the watershed transform. Although oversegmentation is a severe problem for watershed transform, it can contribute to the extraction of weak edges. The information from the presegmentation makes it possible to modify the traditional level set method and to improve its performance. A comparison between the proposed method and the traditional C-V model is shown in the experimental results.

The organization of this paper is described as follows: the new proposed segmentation method is proposed in section 2; the experimental results are shown in section 3; Conclusions and the future work are presented in section 4.

2. THE METHODOLOGY OF PROPOSED SEGMENTATION METHOD

The watershed transform is a morphological gradient-based segmentation technique. The gradient map of the image is considered as a relief map in which different gradient values correspond to different heights. If we punch a hole in each local minimum and immerse the whole map in water, the water level will rise over the basins. When two different body of water meet, a dam is built between them. The progress continues until all the points in the map are immersed. Finally the whole image is segmented by the dams which are then called watersheds and the segmented regions are referred to as catchment basins. Its fast implementation method proposed by L.Vincent and P.Soille in [6] is widely used in the image segmentation field. But the severe oversegmentation problem still exists. The new algorithm will use watershed transform for presegmentation, which has been proved to be very useful in [7]. Although the image is oversegmented, the real boundary is contained in the obtained edges. The advantage of watershed transform is that the resulted small pieces all have closed boundaries. It is very useful for the initialization of the level set method. A threshold can be added to reduce the region numbers.

Level set method represents the curve $C(x,y)$ implicitly in a hypersurface $\phi(C(x,y),t)$ [8]. And the propagating front can be captured by evolving the partial differential equation:

$$\frac{\partial \phi}{\partial t} = F \left|\nabla \phi\right| \quad (1)$$

Where F is the speed function, and it is always constructed by the region information for region-based level set method.

C-V model is the representative region-based level set method [1]. It mainly depends on the mean value of the feature of the regions and functions very well in bi-model segmentation problems. But when the image is more complex, it does not work well. Zhu and Yullie [9] have proposed an interesting model called region competition which uses smoothing and statistical forces to evolve the contour. How to classify a point on the common boundary of two regions is only considered in this paper. It is assumed that there are two regions: object region R_o and background region R_b.They share the common boundary. Each pixel $I(x,y)$ in the either region satisfies the distribution like $P(I_o \mid \alpha_o)$ and $P(I_b \mid \alpha_b)$, where α_o, α_b are the parameters of the object and background distribution respectively. $\vec{c}=(x,y)$ is any point on the boundary and $I_{\vec{c}}(x,y)$ is the image value at that point. According to the principle of the region competition, the motion function of the boundary can be achieved:

$$\frac{\partial \vec{c}}{\partial t} = -\mu k \vec{n} + (\log P(I_{\vec{c}} \mid \alpha_o) - \log P(I_{\vec{c}} \mid \alpha_b))\vec{n} \quad (2)$$

Where μ is a constant, k is the curvature, $\vec{n}$ is the normal vector to the boundary. From Eq. (2), it can be figured out that the smoothing force is determined by the first term. The second term in the bracket decides the statistical force. If the second term is positive, the object region will accept the point as a member, which means that the object region is expanded. On the contrary, if it is negative the object region will be compressed. This kind of competition continues until it converges on the final segmentation image. Thus, region competition becomes more powerful in segmentation. The main idea of our work in this paper is inspired by it. As it has been mentioned above, a piece of object can be extracted and its boundary is adopted as the initial contour of the level set method. Here the level set function is defined as the label level set function $\phi(label)$. Because the label of each pixel of the overpresegmented image is not completely correct and pixels with the same label must have similar property, it does not need to define and compute the level set function of each pixel in the image. The level set function is just defined according to the region numbers, which means that each region has one level set function. And the term of label level set function is defined in order to be distinguished from the traditional one. Inspired by the region competition model, a new region map is then formed. Due to the definition of the label level set function, the original position of the regions is meaningless. Assume that the object and background region all satisfy Guassian distributions. (μ,σ) is the parameter vector, and

$$P(I(x,y) \mid (\mu,\sigma)) = \frac{1}{\sqrt{2\pi}\sigma}\exp\left(-\frac{(I(x,y)-\mu)^2}{2\sigma^2}\right) \quad (3)$$

Then the new segmentation model is proposed as follows:

$$\frac{\partial \phi_i}{\partial t} = \frac{1}{2}\left(\log\frac{\sigma_b^2}{\sigma_o^2} + \frac{(\overline{I}_i-\mu_b)^2}{\sigma_b^2} - \frac{(\overline{I}_i-\mu_o)^2}{\sigma_o^2}\right)\left|\nabla \phi_i\right| \quad (4)$$

Where $\overline{I}_i$ is the mean gray value of the region whose label is i, $i=1,2...N$, N is the number of the presegmented regions. μ_o, σ_o, μ_b, σ_b are the mean value and variance of the object and background regions respectively. The curvature as the smoothing force is not needed. Because the boundary information can be gained from the presegmentation and the boundaries can be obtained naturally when the regions are merged. Because the label level set function has nothing to do with the position, $|\nabla\phi_i|$ in Eq. (4) is defined as:

$$|\nabla\phi_i| = \frac{1}{2}|\phi_o^n - \phi_b^n| \tag{5}$$

which is just like the central difference. The partial differential equation is discretized as follows:

$$\phi_i^{n+1} = \phi_i^n + \Delta t \cdot \frac{1}{2}\left(\log\frac{\sigma_b^2}{\sigma_o^2} + \frac{(\bar{I}_i-\mu_b)^2}{\sigma_b^2} - \frac{(\bar{I}_i-\mu_o)^2}{\sigma_o^2}\right)\cdot\frac{1}{2}\left|\phi_o^n-\phi_b^n\right| \tag{6}$$

Where Δt is the time interval for iteration, ϕ_o^n is the mean of the level set function of the object region and ϕ_b^n is that of the background region. The procedures of the proposed method are described as follows:

(1)Use the watershed transform to presegment the image.

(2)Compute the mean and variance of each presegmented region and choose i ($i = 1,2,3...N$), the label of the object, to get the boundary as the initial contour of the level set method.

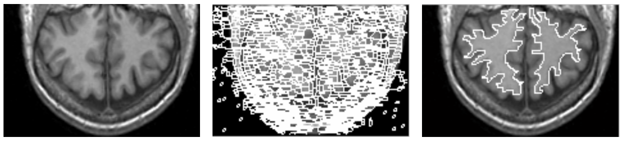
(3)Initialize the label level set function. If the label of the region is equal to i, ϕ_i is set to 0, others are set to -1. So the label level set function on the boundary satisfied the signed distance function.

(4)Update the label level set function according to Eq.(6) until convergence.

(5) Assign the pixel which has the same label to take the same level set function which equals to the certain label level set function. The boundaries of the objects which are the zero level set of the whole image are then obtained.

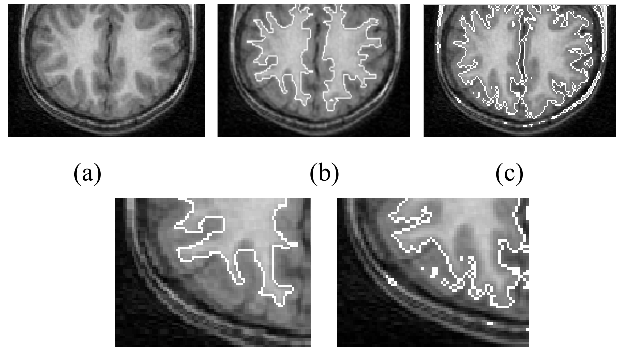
3. EXPERIMENTS AND DISCUSSIONS

The image data from the IBSR(Internet Brain Segmentation Repository) are included to test the accuracy and efficiency of the proposed algorithm. The segmentation results and the comparison between the new method and the C-V model are shown in the following two series of images. The experiments were conducted using MATLAB programming on a Pentium IV platform with 512MB memory.



(a) (b) (c)

Fig. 1 the segmentation process of the proposed algorithm (a) the original image; (b) the result of the watershed transform; (c) the final result of the proposed algorithm



(a) (b) (c)

(d) (e)

Fig. 2 the comparison between the proposed algorithm and the C-V model. (a) the original image; (b) the final result of the proposed algorithm; (c) the result of the C-V model; (d) partial amplification of (b); (e) partial amplification of (c)

Fig. 1(c) and Fig 2(b) have shown that the accurate segmentation of white matter can be obtained from the proposed algorithm. Fig. 2 represents the comparison between the proposed algorithm and the C-V model especially Fig. 2(d) and 2(e). It is clear that the segmentation result is still satisfactory given that the image has weak edges and concave on the edges. The size of Fig. 2 is 146×88. The processing time of the proposed algorithm is 15.24 sec but the cost time of the C-V model is 46.42 sec. Other images from IBSR processed have verified further that the proposed algorithm is nearly two times faster than the C-V model. Therefore, the proposed method has improved the traditional method and has the great promise in large images.

4 CONCLUSIONS AND THE FUTURE WORK

A new algorithm which combines the watershed transform and level set method is proposed in this paper. The method has been applied for medical image segmentation and can extract the nearly accurate boundary even if the image has weak edges and concaves on the edges. It has also been demonstrated that the cost time of the proposed algorithm does not depend on the size of the image but the number of the presegmented region. Experimental results have shown that the proposed method can be effective in dealing with MR brain images with weak edges. It would be better that some prior information and distinguishable features are included for improving the performance of the proposed method in the future work.

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