

ROI Extraction in Dermatosis Images Using a Method of Chan-Vese Segmentation Based on Saliency Detection

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Abstract. Extraction of ROI (Region-Of-Interest) in dermatosis images can be used in content-based image retrieval (CBIR). Image segmentation takes an important part in it. And the performance of the segmentation algorithm directly influences the efficiency of the ROI extraction results. In this paper, a method of Chan-Vese segmentation based on saliency detection to extract the ROI of the dermatosis images is proposed. Firstly the spectral residual approach (SR) [11] is used to get the saliency map of the dermatosis images. Secondly threshold segmentation is used to get the initial ROI images. Finally the Chan-Vese model is used to segment the initial ROI images to get the final ROI images, which can ensure the active contours evolve close to the object and remove the redundant information from the complex background. The experiment results show that the proposed method has the better performance than only using Chan-Vese method.

Keywords: saliency detection, Chan-Vese model, dermatosis images, ROI extraction.

1 Introduction

As one of the important human diseases, in recent years dermatosis more and more effects on human health. Skin color digital images record the information of color, texture and shape of the skin tissues which reflect the distribution of hemoglobin and subcutaneous melanin. They provide vital evidence for medical diagnosis of skin diseases. There have been methods in segmentation of skin cancer dermatoscopic images [1-2] and Psoriasis Skin Images [3-4].

Chinese Disease Question Answering System (Hestia QA) is being developed by Institute of Scientific and Technical Information of China (ISTIC). As a decision support system for dermatosis diagnosis the interface of Hestia QA is flexible and friendly which provide multiple query modes for users to choose. In image query mode people can input their images to know what kind of dermatosis they got. Certainly using the single diagnosis mode we can hardly get the accuracy diagnosis. Hestia QA system combine multiple query mode to give a more accurate diagnosis.

ROI extraction techniques can detect the regions of an image which attract the attention of users. These regions usually contain the higher entropy and can represent

for the whole image. The ROI of the dermatosis images are those diseased tissues which are distinctively different from the other normal tissues in color and texture. Many image segmentation methods are extensively used to extract the ROI of an image. As the most classic and popular region-based active contour model, Chan-Vese model [5].has been successfully used in many types of images especially the two-region images. This model is based on the Mumford-Shah functional [6] for segmentation, and is used widely in the medical imaging field, especially for the segmentation of the brain, heart and trachea [7]. However in the process of the evolution of active contour model the selection of initial contour tend to iterate from the edge of the whole image. Thus it can make the evolution result be influenced by the information of background. At the same time the time it takes is much longer.

In this article we proposed a method of ROI extraction in the dermatosis images using Chan-Vese Segmentation based on saliency detection. These images are from various dermatosis and taken by different mobile device cameras. They usually contain different degree of random noise and have difference in illumination, size, format and so on. The ROI extraction images can be used to Hestia QA image retrieval system for supporting decision.

2 The Chan-Vese Model

The Chan-Vese method [5] is inspired by the Mumford-Shan model Mumford and Shah [6] approximate the image f by a piecewise-smooth function u as the solution of the minimization problem.

Let's denote the region inside C as ω , and the region outside C as $\overline{\Omega} \setminus \omega$. Moreover, c_1 will denote the average pixels intensity inside C , and c_2 will denote the average intensity outside C .

The object of Chan-Vese algorithm is to minimize the energy function $F(c_1, c_2, C)$. Defined by: [6].

$$F(c_1, c_2, C) = \mu \cdot \text{Length}(C) + \lambda_1 \int_{\text{inside}(C)} |u_0(x, y) - c_1|^2 dx dy + \lambda_2 \int_{\text{outside}(C)} |u_0(x, y) - c_2|^2 dx dy \quad (1)$$

Where c_1 and c_2 are constant unknowns representing the average value of u_0 inside and outside the curve, respectively. The parameters μ and λ_1, λ_2 are weights for the regularizing term and the fitting term, respectively.

Minimizing the fitting error in equation (1), the model looks for the best partition of u_0 taking only two values, namely c_1 and c_2 , and with one edge C , the boundary between these two regions, given by $[u_0 \approx c_1]$ and $[u_0 \approx c_2]$. The object to be

detected will be given by one of the regions, and the curve C will be the boundary of the object. The additional length term is a regularizing term and has a scaling role.

For the curve evolution, the level set method has been used extensively, in particular where the motion is governed by mean curvature, as in [8]. This formulation behaves well even with cusps, corners, and automatic topological changes. The motion by mean curvature [8] is given by

$$\begin{cases} \frac{\partial \phi}{\partial t} = |\nabla \phi| \operatorname{div} \left(\frac{\nabla \phi}{|\nabla \phi|} \right), \\ \phi(0, x, y) = \phi_0(x, y), t \in [0, +\infty), (x, y) \in \mathbb{R}^2, \end{cases} \tag{2}$$

Using the Heaviside function H and the Dirac delta function $\delta(z) = \frac{d}{dz} H(z)$, we can rewrite the energy function as follows:

$$\begin{aligned} F(c_1, c_2, \phi) = & \mu \int_{\Omega} \delta(\phi(x, y)) |\nabla \phi(x, y)| dx dy + \lambda_1 \int_{\Omega} |u_0(x, y) - c_1|^2 H(\phi(x, y)) dx dy \\ & + \lambda_2 \int_{\Omega} |u_0(x, y) - c_2|^2 (1 - H(\phi(x, y))) dx dy \end{aligned} \tag{3}$$

Minimizing $F(c_1, c_2, \phi)$ with respect to the constants c_1 and c_2 , for a fixed ϕ , yields the following expressions for c_1 and c_2 , function of ϕ .

$$\begin{cases} c_1 = \text{average}(u_0) & \text{on } \phi \geq 0, \\ c_2 = \text{average}(u_0) & \text{on } \phi < 0. \end{cases}$$

Minimizing the energy $F(c_1, c_2, \phi)$ with respect to ϕ or fixed c_1 and c_2 , using a gradient descent method, yields the associated Euler–Lagrange equation for ϕ governed by the mean curvature and the error terms (see [5] for more details).

3 Proposed Method

3.1 Saliency Map

For an image humans can routinely and effortlessly judge the importance of image regions, and focus attention on the important parts of them, which representative to their querying intention. And most of the remaining regions cannot be interested by them. The salient regions of an image are areas which can most attract the users’ attention and represent for the content of the image. In fact because users also have the different tasks and the prior knowledge they choose the salient regions usually very subjective, getting the different regions as the salient regions of the same image.

Computationally detecting such salient image regions remains a significant goal, as it allows preferential allocation of computational resources in subsequent image analysis and synthesis. Extracted saliency maps are widely used in many computer vision applications including object -of-interest image segmentation, object recognition, adaptive compression of images, content aware image editing, and image retrieval.

The topical method based on visual feature is the saliency map method presented by Itti[9] and others. In the later study many researchers respectively presented many different saliency analysis methods. We used these methods [10-14] to get the saliency maps of our experiment images, and found that the spectral residual approach (SR) method [11] is better than the others because it can generate less noise and extract more ROI.

3.2 Chan-Vese Segmentation Based on Saliency Detection

We chose four different type dermatosis images from Google website, and then used the Chan-Vese model to segment the diseased regions and cannot get a satisfactory result. Considering this we used a method of Chan-Vese Segmentation based on saliency detection to get ROI of the dermatosis images. In the following this model will be introduced.

Step 1: Saliency detection. We used the spectral residual approach (SR) method to get the saliency maps of the images. The results are presented in Section 4.Fig.1.

Step 2: Threshold segmentation. We adopted the threshold segmentation method of the paper [11].

Given $S(x)$ of an image, the object map $O(x)$ is obtained:

$$O(x) = \begin{cases} 1 & \text{if } S(x) > \text{threshold} \\ 0 & \text{if otherwise,} \end{cases}$$

Empirically article [11] set $\text{threshold} = E(S(x)) \times 3$, where the $E(S(x))$ is the average intensity of the saliency map.

In fact the selection of threshold is a trade-off problem between false alarm and neglect of objects. When the threshold is smaller the whole diseased tissues can be extracted. But it also can make a lot of noises, that is, the false alarm is higher. When increasing the threshold the noise can be reduced, but it increase the neglect of objects. The trade-off problem between false alarm and neglect of objects.is that the problem between precision ratio and recall ratio.\

Step 3: Binary image filtering .In order to solve the trade-off problem we dilated the object pixels of the object map obtained by higher threshold segmentation. But while removing the noises which generated in the threshold segmentation, it also brings in some normal skin tissues which surround the diseased tissues. It makes the whole ROI extracted precisely but cannot achieve higher accuracy. Essentially speaking it cannot remove the noise. The results of the initial ROI extraction results are presented in Section 4.Fig.1.

Step 4: Chan-Vese segmentation. In order to get a better result we used the Chan-Vese model to find the accuracy contour of the diseased tissues. Considering

the accuracy of the Chan-Vese segmentation we let the zero pixel regions a pixel value $G(x)$ and got the compensated grayscale images of the initial ROI extraction results.

Given $H(x)$ of the nonzero pixel regions, the intensity of the zero pixel regions $G(x)$ is obtained

$$G(x) = N \times E(H(x))$$

Where the $E(H(x))$ is the average intensity of $H(x)$. The compensated grayscale images are presented in Section 4.Fig.1.

In addition, in Step 3, when dilating the binary images we adopted several approaches, and then used the disk dilation approach. In the end with different parameter combinations we got the better results of the initial ROI extraction results of the dermatosis images. These results are presented in Section 4 .Fig.1.

In Section 4.Fig.2 we presented the comparison results of the final ROI extraction, and compared the iterations and algorithm time of the Chan-Vese method and the proposed method. Apparently the proposed method can reduce the algorithm time and iterations. At the same time it can well improve the precision of the ROI extraction results.

4 Experiment Results

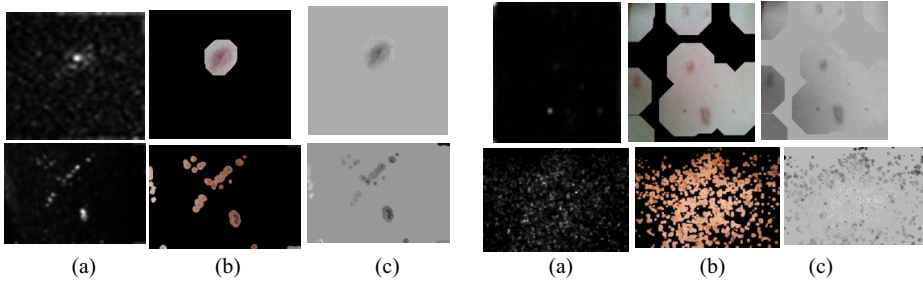


Fig. 1. (a) the saliency maps, (b) the initial ROI extraction results (c) the compensated grayscale images

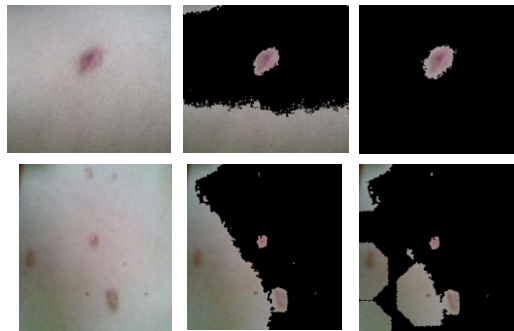


Fig. 2. (a) the original images,(b) the ROI extraction results based on the Chan-Vese method, (c)the ROI extraction results based on the proposed method

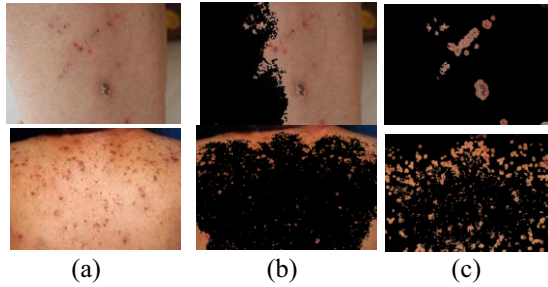


Fig. 2. (continued)

Table 1. The comparison chart of iterations

	Image 1	Image 2	Image 3	Image 4
The Chan-Vese method	160	120	800	800
The proposed method	15	85	250	150

Table 2. The comparison chart of algorithm time

	Image 1	Image 2	Image 3	Image 4
The Chan-Vese method	61.4239s	21.5153s	168.0754s	679.7835s
The proposed method	5.3006s	14.5021s	47.103s	147.083s

5 Conclusions

We discussed the application of Chan-Vese model and the proposed method in ROI extraction of the dermatosis images. With four typical dermatosis images from Google site we used several saliency detection methods to get the saliency maps, found the SR method had the advantage and then used the Chan-Vese model to get accurate results. We separately compare the iterations and algorithm time of the Chan-Vese method and the proposed method. It shows that the proposed method not only get the better ROI extraction results but can well reduce the iterations and algorithm time.

In the future work we will use more dermatosis images and try to find an optimal parameter combination to get the more accuracy ROI extraction results. Considering the noise of the images we will use some denoising method to solve it. Even we can change the Chan-Vese model to get a more accurate result.

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