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Elliptic Object Detection Based on Shape Preserving and Active Contour

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Abstract: We integrate the detected object shape represented by shape restraint equation(s) and general active contour models into a unified energy function to generate the shape preserving active contour model, which keeps the curve to be a specific class shape in the evolvement. In this model, a specific class contour shape is represented as the zero level line of some certain parametric level set function(s). So, this model can not only detect the given object correctly but also characterize the object shape quantificationally via these parameters. In addition, we build an energy functional for elliptic objects detection using the proposed model, deduce the corresponding Euler-Lagrange ordinary differential equation (ODE(s)) of its shape parameters and implement them using level sets method. The elliptic object detection model has many applications such as papilla segmentation, iris detection and camera calibration. By numerical experiments presented in the paper, it can not only detect the elliptic objects correctly but also is robust to noise, deformity and occlusion etc.

Key words: shape preserving; elliptic object; active contour; Chan-Vese model; level set

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基于形状保持主动轮廓的椭圆状目标检测

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摘要：本文通过形状约束方程(组)与一般主动轮廓模型结合，将目标形状与主动轮廓模型融合到统一能量泛函模型中，提出了一种形状保持主动轮廓模型即曲线在演化过程中保持为某一类特定形状。模型通过参数化水平集函数的零水平集控制演化曲线形状，不仅达到了分割即目标的目的，而且能够给出特定目标的定量描述。根据形状保持主动轮廓模型，建立了一个用于椭圆状目标检测的统一能量泛函模型，导出了相应的 Euler-Lagrange 常微分方程并用水平集方法实现了椭圆状目标检测。此模型可以应用于眼底乳头分割，虹膜检测及相机标定。实验结果表明，此模型不仅能够准确的检测出给定图像中的椭圆状目标，而且有很强的抗噪、抗变形及遮挡性能。
关键词：形状保持；椭圆状目标；主动轮廓；Chan-Vese 模型；水平集

1 Introduction

Image segmentation is a fundamental research topic in image processing, which utilizes information as much as possible to segment a given image into several desired and meaningful parts, including the low-level information and prior knowledge information such as shape, texture and homogeneous regions. Since Osher and Sethian proposed level set methods and variational framework[1] in image segmentation, the incorporation of these information in a variational framework has become a focus research in the area at present, for it is robust to noise,

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occlusion and deformity etc.

Numerous approaches have been proposed on image segmentation using level set methods [1], M-S model [2] and prior shape [3]. In ref [4], it incorporated a shape energy into M-S model[2], which penalized the deviation of active contour control point vector from the learning vector space. In ref [5], Cremers developed a very useful model for knowledge-driven segmentation by introducing a labelling function to indicate the region in which the prior shape should be enforced; however, the model is pose invariant. Chan in ref [6] solved the problem by building an equivalent relation of two objects with the same shape represented by signed distance functions. Moreover, Cremer in ref [7] solved the problem of discriminating familiar objects from unfamiliar objects in a given image by means of a vetor-valued labelling function, like as ref [8] using the multiphase level set. These mentioned models are to find an object or objects in a given image whose shapes are the same as the prior shape via translation, rotation and scaling; however, in some cases, especially in a series of images, the object shape is variant. For example, when an object is imaged at different views or different time, its shape in images may be changed. Because the prior shape is invariant in these models, they failed to get correct segmentation results if the object shape is variant. So the definition of the same shape using signed distance function in the above models is not flexible enough and should give a broader definition of prior object shape that is not invariant.

In this paper, we propose a shape preserving active contour model for elliptic object detection[9]. In our model, the prior object shape is represented by a mathematical function with parameters. The prior object shape is controlled by its parameters and does not keep invariant. With level set and variational formulation our new model can detect any elliptic shape object in an image.

The outline of the remainder paper is as follows: In section 2, we propose the principle of the shape preserving active contour model. In section 3, the model for elliptic object detection is presented. Some experiment results and applications are shown in section 4. In section 5, we discuss some limitations of our model, present some ideas directing our future work and end this paper with a conclusion.

2 Shape Preserving Active Contour Model

Any object can be represented uniquely by a signed distance function – a special level set function and vice versa [6]. Given an object $O \subset R^2$, which is assumed to be closed and bounded, then it can be uniquely represented by a signed distance function ϕ as follows:

$$|\nabla\phi| = 1, \quad \phi\begin{cases} > 0 & X \in O \setminus \partial O \\ = 0 & X \in \partial O \\ < 0 & X \in R^2 \setminus O \end{cases} \tag{1}$$

Essentially, the shape preserving active contour model is keeping the evolving contour ϕ to be a specific class prior shape, achieving that the segmentation result is the demanded object and providing correspoinding shape parameters. The fundamental formulation of it can be expressed as follows:

$$\min_{\phi} \int_{\Omega} F(\phi(T_s), |\nabla\phi|, u_0, |\nabla u_0|)\,\mathrm{d}\boldsymbol{x}, \quad \text{subject to}: \underbrace{\|\phi(T_s) - T_s(\phi_0)\| \le \varepsilon}_{\text{shape restra int}} \tag{2}$$

where F is the general active contour energy function, ϕ and u_0 are the level set function and the input image respectively, ϕ_0 is the prior shape, T_s is the shape transformation operator for a specific class prior shape and ε is the measurement of difference between shapes. When $\varepsilon = 0$, it becomes the shape preserving active contour model, i.e. keep the evolving the curve to be a specific class shape.

3 Elliptic Object Detection Model

Obviously, an elliptic object can be represented by a special level set using its mathematical expression as bellow:

$$\phi = 1 - \sqrt{\frac{[(x-x_0)\cos\theta + (y-y_0)\sin\theta]^2}{a_0^2} + \frac{[-(x-x_0)\sin\theta + (y-y_0)\cos\theta]^2}{b_0^2}} \tag{3}$$

where (x_0, y_0) is the center of the ellipse, θ the angle of rotation and (a_0, b_0) are essentially the scaling factors that represent the length of semi-major axis (semi-minor axis) and semi-minor axis (semi-major axis) respectively.

Therefore, the elliptic object detection model based on Chan-Vese's[10] model can be written as:

$$\inf_{c_1,c_2,\phi}\{E[c_1,c_2,\phi\,|\,u_0]\} = \lambda_1\int_\Omega (u_0-c_1)^2 H(\phi)\mathrm{d}x\mathrm{d}y + \lambda_2\int_\Omega (u_0-c_2)^2(1-H(\phi))\mathrm{d}x\mathrm{d}y \tag{4}$$

$$\text{subject to}: \phi = 1 - \sqrt{\frac{[(x-x_0)\cos\theta + (y-y_0)\sin\theta]^2}{a_0^2} + \frac{[-(x-x_0)\sin\theta + (y-y_0)\cos\theta]^2}{b_0^2}}$$

where $\lambda_1>0$, $\lambda_2>0$ are weighting parameters of the two terms and $H(\phi)$ is the Heaviside function. Comparing with Chan-Vese's model, our model has an added constraint equation (3), which can be thought as the prior shape restraint. Due to the smoothness ϕ, here we do not use the length term in C-V model [6]. For more details about C-V model see ref [10].

Let us give following denotations:

$$\begin{aligned} A &= (x-x_0)\cos\theta + (y-y_0)\sin\theta \\ B &= -(x-x_0)\sin\theta + (y-y_0)\cos\theta \end{aligned} \tag{5}$$

Then, the evolution equations related to the Euler-Lagrange equations for Eq. (4) are:

$$\frac{\mathrm{d}a_0}{\mathrm{d}t} = -\int_\Omega [\lambda_1(u_0-c_1)^2 - \lambda_2(u_0-c_2)^2]\,\delta(\phi)A^2\frac{1}{a_0^3}\mathrm{d}x\mathrm{d}y \tag{6}$$

$$\frac{\mathrm{d}b_0}{\mathrm{d}t} = -\int_\Omega [\lambda_1(u_0-c_1)^2 - \lambda_2(u_0-c_2)^2]\,\delta(\phi)B^2\frac{1}{b_0^3}\mathrm{d}x\mathrm{d}y \tag{7}$$

$$\frac{\mathrm{d}x_0}{\mathrm{d}t} = -\int_\Omega [\lambda_1(u_0-c_1)^2 - \lambda_2(u_0-c_2)^2]\,\delta(\phi)[\frac{A\cos\theta}{a_0^2} - \frac{B\sin\theta}{b_0^2}]\,\mathrm{d}x\mathrm{d}y \tag{8}$$

$$\frac{\mathrm{d}y_0}{\mathrm{d}t} = -\int_\Omega [\lambda_1(u_0-c_1)^2 - \lambda_2(u_0-c_2)^2]\,\delta(\phi)[\frac{A\cos\theta}{a_0^2} + \frac{B\sin\theta}{b_0^2}]\,\mathrm{d}x\mathrm{d}y \tag{9}$$

$$\frac{\mathrm{d}\theta}{\mathrm{d}t} = -\int_\Omega [\lambda_1(u_0-c_1)^2 - \lambda_2(u_0-c_2)^2]\,\delta(\phi)AB[\frac{1}{b_0^2} - \frac{1}{a_0^2}]\,\mathrm{d}x\mathrm{d}y \tag{10}$$

where $\delta(x)$ is the Dirac function. By the numerical solution of the evolving parameters through above equations, any shape elliptic object can be segmented and detected, regardless of the change of the ratio of a_0 to b_0.

The evolving equation of the elliptic object can also be written as:

$$\frac{\partial\phi}{\partial t} = \frac{\partial\phi}{\partial \boldsymbol{P}} \bullet \frac{\mathrm{d}\boldsymbol{P}}{\mathrm{d}t} \qquad \text{where} \qquad \boldsymbol{P} = [a_0, b_0, x_0, y_0, \theta]^{\mathrm{T}} \tag{11}$$

If we only want to detect the disc object in images, the shape restraint (3) can be substituted by the following shape restraint:

$$\phi = 1 - \sqrt{(x-x_0)^2/r_0^2 + (y-y_0)^2/r_0^2} \tag{12}$$

where r_0 and (x_0, y_0) denote a circle's radius and centre coordinate respectively. Because for the circular object $a_0 = b_0 = r_0$ and $\theta = 0$. The related evolution equations for its parameters can be written as follows:

$$\frac{\mathrm{d}r_0}{\mathrm{d}t} = \frac{\mathrm{d}a_0}{\mathrm{d}t} + \frac{\mathrm{d}b_0}{\mathrm{d}t} = -\int_\Omega [\lambda_1(u_0-c_1)^2 - \lambda_2(u_0-c_2)^2]\delta(\phi)\frac{1}{r_0}\mathrm{d}x\mathrm{d}y \tag{13}$$

$$\frac{\mathrm{d}x_0}{\mathrm{d}t} = -\frac{\partial E}{\partial x_0} = -\int_\Omega [\lambda_1(u_0-c_1)^2 - \lambda_2(u_0-c_2)^2]\delta(\phi)\frac{A}{r_0^2}\mathrm{d}x\mathrm{d}y \tag{14}$$

$$\frac{\mathrm{d}y_0}{\mathrm{d}t} = -\frac{\partial E}{\partial y_0} = -\int_\Omega [\lambda_1(u_0-c_1)^2 - \lambda_2(u_0-c_2)^2]\delta(\phi)\frac{B}{r_0^2}\mathrm{d}x\mathrm{d}y \tag{15}$$

Generally, the elliptic shape restraint can be substituted by other shape restraints, such as polygon restraint, according to the shape of the objects to be detected.

4 Experiment Results

In this section we present some experiments and applications to validate our model for elliptic and disc object detection respectively. In these numerical experiments, the time step is Δt = 0.1 and the intensity range of input image is [0, 1]. Firstly, we implement our model for automatic detection of papilla contour in fundus images. In fundus images the papilla appears as a bright or yellowish region. Its shape appears more or less as a circle or an ellipse. Its size and shape varies from image to image. For the diagnosis of eye diseases, such as glaucoma, the ophthalmologists concentrate on the area around the papilla and pay most of their attention to changes in the region. Therefore, both the identification and shape analysis of the papillae in fundus images are very important for computer aided diagnostics. For the colour RGB fundus images the contour of the papilla to appear more continuous and less disturbed by the black vessel in the red channel in RGB colour space. Therefore the red channel is usually used for papilla contour detection (see Fig.1). Some results of papilla segmentation with our model are shown in Fig.1. In numerical implementation of equation (4), we choose λ_1 =1, λ_2 =1 and the discrete time step of the equation (10) is $0.01\Delta t$ for its small scale.

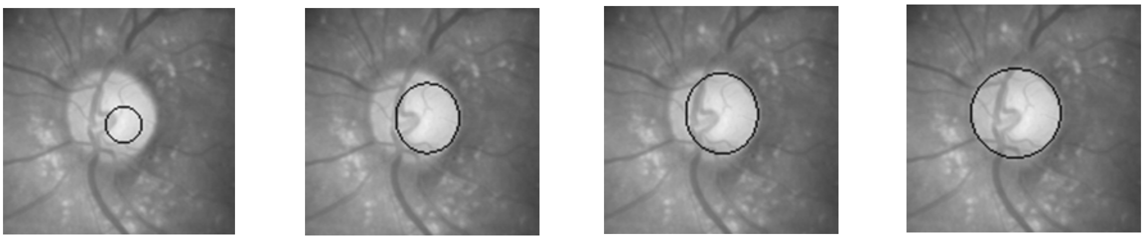

Fig.1 Papilla detection using our model. Image size: 131×128, Initial contour: a_0 = 10, b_0 = 10, x_0 = 69, y_0 = 66, θ_0 = 0. The first and the last one are the initial and final step respectively. The middle ones are the middle steps

Because the papilla shapes in fundus images are not invariant, the C-V model prior to shape, in which the prior shape is invariant, is not suitable for the papilla segmentation. As the comparison test, we used the original C-V model to segment the papilla region. Some results are shown in Fig.2. The segmentation results depend upon the regularizing parameter μ in C-V model[10].

The papilla region sometimes is not correctly segmented with some values of μ. Although for a fundus image we can adjust the parameters μ to obtain the correct segmentation in some cases (see the right image in Fig.2), it is impossible to determine fixed value of the parameter, or determine adaptively its value, in C-V model for the automatic correct papilla segmentation within a broad variety of fundus images. The same problem exists among other methods such as snake, active contour based on image gradient and etc.

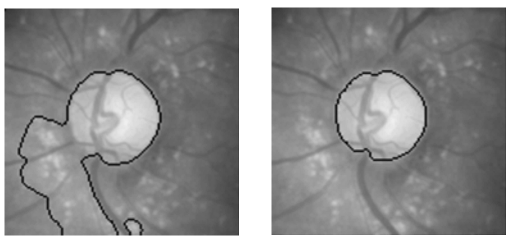

Fig.2 Papilla detection without prior shape based on Chan-Vese's model. The values of μ are 0.04×255^2 and 0.06×255^2 for the left and right images respectively.

Another four papilla segmentation experiments using C-V and our model respectively are shown in Fig.3. The experiment results shown that our method is more effective in the automatic segmentation of fundus images. Another advantage of our model is that after the segmentation it can directly provide the shape parameters of the papilla region, such as the lengths of the major and minor axes, the centre location, the rotation angle and other geometric parameters, which are important for the computer aided diagnostic of eye diseases.

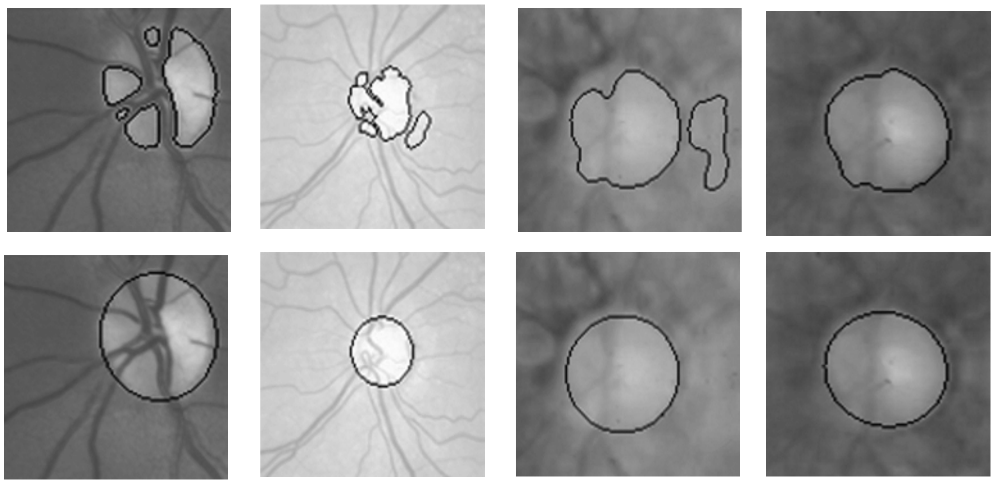

Fig.3 Four papilla segmentation results with C-V and our model. The first and second rows represent segmentation results with C-V and our model respectively. Each column represents segmentation results with C-V and our model on the same image respectively.

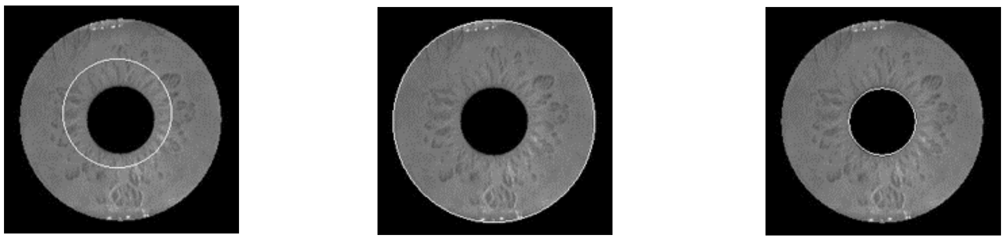

Fig.4 Iris boundaries detection. Image size: 217×210, Initial contour: r_0 = 50, x_0 = 105, y_0 = 100, Parameters for exterior boundary location: λ_1 = 1, λ_2 =1. Parameters for interior boundary location: λ_1 = 3, λ_2 =1. The order is from left to right. The first one is the initial contour. The second and the last one are results of exterior and interior boundary locations of an iris respectively using our model.

Secondly, we give an experiment for iris detection by a circular shape restraint. In Fig.4, we implement our model on iris exterior and interior boundaries detection [11]. Through the experiment, we can see that the circular shape restraint model is effective for iris recognition. We can see that the ratio of λ_1 to λ_2 controls the location of final circle. If $\lambda_1>\lambda_2$ the first term in equation (4) that is the interior region energy becomes the major term and vice versa.

5 Conclusion and discussion

In this paper, we propose a shape preserving active contour model for elliptic object detection. In our model an elliptic shape restraint is used to segment automatically and flexibly elliptic objects with different shapes in images. Compared with the C-V model prior to invariant shape, it allows for the shape variant of objects to be detected. We presented some applications and experiments of our model in this paper. They proved its effectiveness and flexibility. Generally, other shape restraints, such as polygon shape restraint, could be used in our model according to the shape of objects to be detected. We think that the C-V model prior to general polygon shape restraint and other restraints would be possible through our simple tests on quadrangle or pentagon shape restraint. The limitation of our model is that it can only detect one object. Besides, if the object to be detected is very small and in a given image there exist other larger different objects, the detection result depends on the choosing of the initial contour. These mentioned problems could be solved via introducing_multiphase level set and the dynamic vector-valued labelling function, like as ref [7].

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