ADAPTIVE CONTOUR MODEL USING TEXTURE FEATURE VECTORS

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ABSTRACT

In this paper we consider both the problem of fitting and tracking an amorphous object in a plane. In evaluating these problems, we propose a physically based approach using an *active contour model*. We define a *texture feature vector* and apply it to the *active contour model*. In addition, we make the model adaptive. A method for changing the topology which allows even automatic contour splitting into two or more parts is shown. We discuss in detail how the various parameters and forces of the *active contour* can be selected. To promote the convergence of the iteration process, we employ a time-varying damping factor. The proposed adaptive contour model has been successfully applied to the contour extraction process from a sequence of microscopic images, and also to the study of deformations along the cross-sections.

INTRODUCTION

This paper elaborates upon a number of issues related to with the development of techniques to permit fitting and tracking of deformable objects in a plane.

More specifically, we are interested in the visual fitting of *deformable contours* to the cross-sections of biological organs as their boundaries move and deform along a series of cross-sections. We regard such biological organs as ideal amorphous objects because their boundaries can deform slightly from one section to the next. The series of microscopic cross-sections can be viewed as a temporal series of images; the dynamics of boundaries can then be characterized by time-dependent variations in position and shape.

CONTOUR FITTING PROBLEM

We are attempting to address two problems related to computer vision:

1. The problem of segmentation of an image and selection of significant properties.
2. The description of the shape of an amorphous object in both the static and dynamic cases.

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The essential contribution of this paper to the solution of problem 1) is the proposed representation of an image with its field of *feature vectors* defined on textures. Problem 2) was originally solved using an *active contour model* (ACM), a solution proposed by Kass *et al.* (1987). We examine and extend this model to an adaptive one capable of shrinking and splitting into several parts.

An ACM can be represented as an energy-minimizing spline controlled by image forces such as lines, edges and textures. Moreover, internal forces impose smoothness constraints on the spline. The spline, therefore, finally models the boundary of an organ.

PROBLEMS AND NEW APPROACHES

The original model proposed by Kass *et al.* suffers from some difficulties that require clarification:

- The ACM has several parameters: elasticity, mass, damping constant and weight functions w_i, $i = 1, \ldots, 4$ [5],[6]. The problem is how to select them.
- An initial estimate of the contour is necessarily selected as close as possible to the object boundary, especially for concave objects.
- The ACM iteration process prefers the solutions of the shortest length, in other words, the ACM naturally tends to shrink.
- There are also some problems including numerical instability; improvements and discussions concerning stability can be found in [3],[6].

We discuss the above difficulties and propose a new ACM based on a *texture representation* of an image. We consider an image divided into the small lattices $M \times M$, and each lattice is a texture represented as a stochastic two-dimensional field. A texture model is a mathematical procedure capable of producing and describing a textured image. Furthermore, for each lattice a 7-dimensional vector, called a *texture feature vector*, consisting of the parameters of the texture model is defined. Various proposed improvements can be summarized as follows:

- Instead of using only a scale space representation of an image, defined in [7], we propose to use a texture representation of the image in addition to scale space. This kind of representation moves the ACM close to the border between two different types of textures. As a texture representation, we employed the "Simultaneous Autoregressive Model" (SAR), a model that is well researched in [4].

- We extended the potential energy of the ACM, employing both the proposed texture edge energy and area energy.
- Because of the newly proposed ACM, we define new parameters and introduce new rules for setting the parameters adaptively.
- To promote the convergence of the iteration process, we employ a time-varying damping factor $\gamma(t)$.
- We make the ACM adaptive, in other words, the rules for inserting and deleting a point in the ACM are defined. Furthermore, we have developed a method for altering the ACM topology by fulfilling the rule of contour division.

New Active Contour Model

An ACM is a deformable curve composed of abstract elastic materials. Consider an ACM $v(s,t) = (x(s,t), y(s,t))$ with a spatial parameter s and time t defined on intervals Ω and T, respectively. Let $I(x,y,t)$ denote the image intensity at position (x,y) in time t. The potential energy function of the ACM is defined in [5]. On addition, the new energy terms $E_{texture}$ and E_{area} are defined. The total energy is then written as

$$\begin{aligned} E_{snake} &= \frac{1}{2}\int_{\Omega} \{E_{int}(v) + E_{image}(v) \\ &+ E_{texture}(v) + E_{area}(v)\}\, ds. \end{aligned} \qquad (1)$$

Denoting w_i $(i = 1, \ldots, 6)$ as the weight parameter for each energy term, we employ the following energy terms in the total energy, whereas the first two of them have been proposed in [5],[8].

1. *Internal potential energy,* i.e., first- and second-order continuity terms

$$E_{int} = w_1(s)\|v_s\|^2 + w_2(s)\|v_{ss}\|^2, \qquad (2)$$

where subscripts denote the partial derivatives.

2. *The image energy* as a combination of image intensity and gradients of intensity smoothed by Gaussian filter

$$E_{image} = w_3 I(x,y) + w_4\|\nabla(G_\sigma \star I(x,y))\|^2. \qquad (3)$$

3. Any small lattice $M \times M$ within the image is represented as an SAR model appropriate for texture description. The parameter estimations of the SAR model defined on a lattice are collected into a vector

$$\begin{aligned} F &= (\hat{\Theta}(0,1), \hat{\Theta}(1,0), \hat{\Theta}(1,1), \hat{\Theta}(-1,-1), \\ &\quad \hat{\rho}_{N_1}, \hat{\rho}_{N_2}, \mu_\Omega) \end{aligned}$$

called a *texture feature vector* introduced by Ďurikovič *et al* (1994). A *texture feature vector* is defined for each point (x,y) within the image domain. Parameters $\{\hat{\Theta}(0,1), \hat{\Theta}(1,0), \hat{\rho}_{N_1}\}$ and $\{\hat{\Theta}(1,1), \hat{\Theta}(-1,-1), \hat{\rho}_{N_2}\}$ are obtained by the horizontal and vertical texture information, respectively [4]. μ_Ω, denotes the mean in the lattice $M \times M$.

Based on the above definition of the *texture feature vector*, we propose the new *texture potential energy* for separation of textures as

$$E_{texture} = w_5\mu(F_v, F_n^+), \qquad (4)$$

in other words, a similarity measure μ between the 7-dimensional *texture feature vectors* F_v and F_n^+. Where F_v is a *texture feature vector* at point $v(s,t)$, while F_n^+ is a vector at the auxiliary point $V_n^+(s,t)$ derived from $v(s,t)$ as

$$V_n^+(s,t) = v(s,t) + \xi N_s,$$

where N_s is the outward contour normal at point $v(s,t)$, and $\xi > 0$ is a small constant.

4. A new *area term* defined as

$$E_{area} = \frac{w_6}{2}\begin{vmatrix} x_1 & x_2 \\ y_1 & y_2 \end{vmatrix} + \ldots + \frac{w_6}{2}\begin{vmatrix} x_N & x_1 \\ y_N & y_1 \end{vmatrix} \qquad (5)$$

for a non-selfintersecting *active contour* with spatial discretization carried out by sampling of contour v into N nodes, $\mathbf{v}_i = (x_i, y_i)$ $(i = 1, \ldots, N)$. This term makes the ACM shrink or grow like a balloon according to the sign of w_6.

Dynamics

Given the potential function (1), an active contour model is described by its position $v(s,t)$, velocities $\frac{\partial v}{\partial t}(s,t)$, and accelerations $\frac{\partial^2 v}{\partial t^2}(s,t)$ of its mass elements as a function of parameters s and time t. According to Newtonian law expressed by Lagrange's equations of motion, the dynamics of each vertex $v(s,t)$ is expressed by

$$\mu\frac{\partial^2 v}{\partial t^2}(s,t) + \gamma\frac{\partial v}{\partial t}(s,t) + F_{int} = F_{ext}, \qquad (6)$$

where $\mu(s)$ and $\gamma(s)$ are mass density and damping factor, respectively; force F_{int} is introduced to make the contour continuous, while F_{ext} corresponds to external forces. Both F_{int} and F_{ext} depend on contour position $v(s)$ and time t.

The internal force F_{int} is derived from a nonnegative potential energy $E_{int}(v)$ as its variational derivate,

$$F_{int} = \frac{\delta E_{int}(v)}{\delta v},$$

and represents the elastic force at each contour point.

The fitting and tracking process of the *active contour* is controlled by a field of external forces given as a sum of the gradients of energies (3),(4), and (5):

$$F_{ext} = W_I\nabla E_{image} + \nabla E_{texture} + W_A\nabla E_{area}.$$

Adaptive weight functions W_I and W_A control the strength of the *image* and *area* forces, respectively.

Discretization and Adaptive Damping Factor

A simplified Eq. 6 is obtained by setting the mass density $\mu(s)$ to zero, while preserving the dynamics:

$$\gamma \frac{\partial v}{\partial t}(s,t) + F_{int} = F_{ext}.$$

This model is sufficient to computer vision applications that involve the fitting and tracking of a contour to image data.

Let us first consider the discretization of the *active contour model* in both domains of space and time. The space discretization is done by sampling the function $v(s)$ into N nodes, leading to the N-dimensional vector $\boldsymbol{v}$. The time discretization is achieved similarly by a time step Δt. Thus, the forces F_{int} and F_{ext} are discretized as N-dimensional vectors $\vec{\boldsymbol{F}}_{int}$ and $\vec{\boldsymbol{F}}_{ext}$. The discrete vector $\vec{\boldsymbol{F}}_{int}$ can be written in the matrix form $\vec{\boldsymbol{F}}_{int} = \boldsymbol{K} \cdot \boldsymbol{v}$, where $\boldsymbol{K}_{N \times N}$ is known as a stiffness matrix. This, clearly leads to the numerical integration of the equation of motion. To obtain the precise solution quickly, the first-order Euler method is implemented. The position of *active contour* $v(s,t)$ is then updated according to the expression

$$\boldsymbol{v}^{t+\Delta t} = \boldsymbol{v}^t + \Delta t \gamma^{-1} (\vec{\boldsymbol{F}}^t_{ext} - \boldsymbol{K} \cdot \boldsymbol{v}^t). \qquad (7)$$

Speeding the Iteration Process

The damping factor γ controls the stability and speed of the iteration process given by Eq. 7. As in the steepest descent method [1], we established parameter γ as a dependent of time, i.e. $\gamma = \gamma(t)$. For each time step, we define $\gamma(t)$ from the condition for the minimum of the equation

$$\Psi(\gamma^t) = E_{snake}(\boldsymbol{v}^t - \Delta t \gamma^t \nabla E_{snake}(\boldsymbol{v}^t)),$$

where the gradient of the potential energy is derived as $\nabla E_{snake} = \boldsymbol{K} \cdot \boldsymbol{v}^t - \vec{\boldsymbol{F}}^t_{ext}$.

At each time step we have to solve the equation $\Psi'(\gamma^t) = 0$ with one unknown γ^t. This can be done by one of the numerical methods used for the solution of high-degree algebraic equations. We have used the Newton-Raphson method with success. Should there be other minima in the neighborhood of required solution v, and should the choice of v^0 not be made well, the process diverges and will not lead to the required solution. In that case, this problem is overcome by a skillful choice of initial solution v^0.

Adaptive Parameters

We will now consider how to fix the snake parameters W_I and W_A in the discrete domain. Let us first define the *shrinking part* of the contour as where the image forces gain less magnitude.

The weight, W_A, for *area force* scales the magnitude of *area force* with a nonzero value along the shrinking part of the contour, while for the other parts the *area force* is set to have a magnitude of zero. Consequently, we propose the parameter W_A as a continuous function of θ along the active contour $v(s)$, written as

$$W_A(\theta) = \begin{cases} \frac{1}{2} + \frac{1}{2}\cos\frac{\pi\theta}{L} & \theta < L \\ 0 & \text{otherwise} \end{cases} \qquad (8)$$

where L is a parameter controlling the vanishing of the area force, and $\theta = |\nabla E_{image}(v(s))|$ denotes the norm of the image force given at a contour point $v(s)$.

The image intensity in the narrow area around the *shrinking part* of the contour is not usually a constant value but has a small variation due to the noise distribution. It arises in the small magnitudes of image forces $|\nabla E_{image}|$ that should be neglected till they exceed a certain threshold value L_0. In this sense and similar to the introduction of W_A, we introduce the parameter W_I, written as

$$W_I(\theta) = \begin{cases} 1 - W_A(\frac{L}{L-L_0}(\theta - L_0)) & L_0 < \theta < L \\ 0 & \theta \le L_0 \\ 1 & \text{otherwise} \end{cases} \qquad (9)$$

where L_0 and L are parameters controlling the vanishing interval of image force.

Parameter L_0, in our implementation, is selected by the method whereby the image force at a certain point is neglected till at least 90% of the area force magnitude at that point is applied in Eq. 6. This leads to $L_0 = \frac{L}{\pi} \arccos 0.8$. Due to space limitations, we will note simply that parameter L is also estimated automatically from the histogram of values θ along the *active contour*. The automatic estimations result in $L = 8.01$ in the case of Fig. 3, with good shrinking behavior. A plotted graph of the weight functions $W_A(\cdot)$ and $W_I(\cdot)$ is illustrated in Fig. 1.

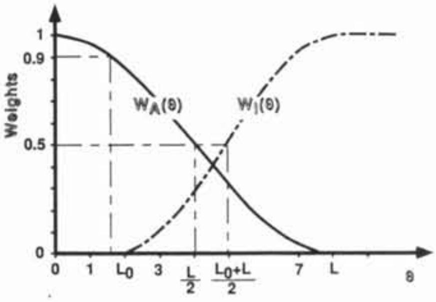

Figure 1: Weight function, W_A, of the area force and the weight function, W_I, of the image force used with parameters $L = 8$ and L_0 as discussed above.

Changing the Topology of ACM

In this section, we address basic operations for the automatic creation of a contour topology. For a single contour point, the operations of adding and deleting are the most fundamental. For the entire contour, the operation of a contour division into n parts is proposed. Assuming that the contour points are in a near-equilibrium configuration with respect to the internal potentials, topology operations are defined as the following heuristic rules.

1) *Adding a Single Point:* If the distance between two points $\boldsymbol{v}_i$, $\boldsymbol{v}_{i+1}$ satisfies the criterion $d_{min} \leq |\boldsymbol{v}_i - \boldsymbol{v}_{i+1}| \leq d_{max}$, a new point is created between the two points. Typically used thresholds are $d_{min} \approx 1.7\bar{d}$ and $d_{max} \approx 2.5\bar{d}$, where $\bar{d}$ is the average inter-point distance.

2) *Deleting a Single Point:* If two neighbor points are separated by a distance D such that $D < D_{min}$, one of these points is deleted. We have experimented with $D_{min} \approx \frac{1}{4}\bar{d}$.

3) *Division of a Contour:* If two points $\boldsymbol{v}_i$ and $\boldsymbol{v}_j$ satisfy the following conditions, then a contour is divided into two parts by the segment $\boldsymbol{v}_i\boldsymbol{v}_j$;

- $|\boldsymbol{v}_i - \boldsymbol{v}_j| \leq d_{cut}$, where d_{cut} is a constant.
- The projections of vectors ∇E_{area} at points $\boldsymbol{v}_i$ and $\boldsymbol{v}_j$ onto the vectors $\overrightarrow{\boldsymbol{v}_i\boldsymbol{v}_j}$ and $\overrightarrow{\boldsymbol{v}_j\boldsymbol{v}_i}$, respectively, have opposite directions.

Moreover, a contour is divided recursively into n parts if n pairs obeying the above conditions exist.

Obtained Results

The proposed adaptive ACM was implemented on a *Silicon Graphics Workstation Indigo* (85 MIPS) and embedded in a reconstruction system from a set of cross-sections already developed. Compared to the classical ACM, the accuracy of the results improved, especially in those parts of the image where only a small difference exists between the texture patterns of the observed object and surrounding objects. At the same time, the computation time was decreased and the convergence rate improved due to the time-varying damping factor $\gamma(t)$.

One of the original images scanned from the microscope and the final position of the ACM are shown in Fig. 2. The example in Fig. 3 shows 26 microscopic cross-sections with $7\mu m$ inter-slice distance. We fit the adaptive ACM to a series of images from bottom to top, starting from one closed contour. While moving and tracking the contours from slice to slice, new points are automatically inserted to get better results for concave parts of the object. Consequently, the adaptive ACM splits into three parts and the tracking of each part continues, separately.

The proposed adaptive ACM has been successfully applied to the reconstruction process from a set of microscopic images, and also to the study of deformations along the cross-sections.

Conclusions

In this paper, the improvement and extension of ACM for fitting contours to the boundaries of amorphous objects have been proposed. Our adaptive ACM provides more accurate solutions for concave parts of an object, while changing its topology, as well as an improvement in the convergence rate of the ACM iteration procedure.

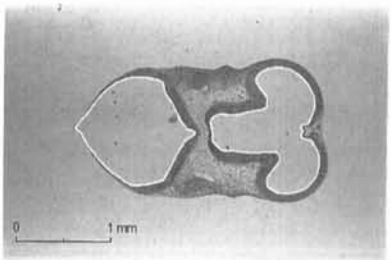

Figure 2: An example of the original image related to the fitting process.

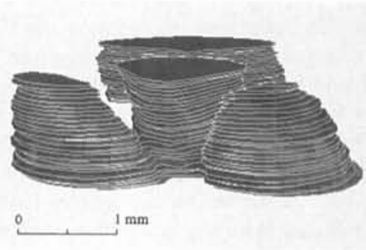

Figure 3: Tracking the brain of a mouse embryo through cross-sections visualized as a stack of contours. The scale for all axis directions is the same.

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