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A Novel Elastic Contour Model for Locating Objects in Images

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Abstract

This paper presents an active method for locating objects in images, which is conceptualized mainly by elastically deformable contour model. When an initial model is applied to an image data, it attracts near dominant image features such as edges or lines, but tries to keep its home shape or smooth the deformation if a deformation from the home shape occurs. This model is characterized by the core and the rigidity coefficients which control the shape and strength with the prior knowledge about the expected shape of the object. This mechanism significantly improves the performance of detecting object boundaries in presence of some disturbing image features. The proposed method is validated through a series of experiments, which include tracking objects under non-rigid motion and comparison with the original snake models.

1. INTRODUCTION

In Automatically locating objects of interest in an image is one of the most important steps leading to the analysis of image data. These tasks are often likely to be disturbed by certain distortions or variations which are encountered in the image-formation process. These include sensor noise during the image processing, perspective distortions, variations in photo-metric or background conditions, concealment of target objects by other objects, and the image deformation of target objects. These problems can be solved easier if models of the geometric properties of the object are available.

To achieve the goal, a number of matching techniques using elastic models[1-4] have been developed during the past decades. Some of the approaches have been proven to have successful results, but they still encounter some difficulties. The models used in most approaches have a number of parameters to control the shape, pose, or scale of the model, making the modeling processes time-consuming and cumbersome. These usually require a well-developed high-level modeling mechanism to ensure an acceptable result. Moreover, the fitting or matching algorithms to recover the models become computationally complex and difficult to numerically implement. To avoid those problems, Kass *et al.*[5] presented a flexible contour model, called snake model, which is basically controlled by continuous splines. The model easily represents almost smooth boundaries, which can be explored through interaction with the model. Although this work is more computationally efficient compared with the previous approaches, it still encounter several limitations, which are discussed in the section 2. Amini *et al.* [6] proposed a dynamic programming algorithm for minimizing the energy functional that introduces hard constraints to achieve more desirable behavior of the snake model. However, the algorithm suffers from rapidly increasing computational complexity as the number of the control points and the size of the neighborhood increase. Cohen[7] proposed an energy minimizing contour model in which the contour behaves like a balloon inflated by an additional force. Williams *et al.*[8] proposed a greedy algorithm which is faster than the dynamic programming but has a reliability problems compared with the snake or the dynamic programming algorithms. In the recent years, the snake models have been successfully applied to various vision computing areas: low-level image processing with image segmentation[9] and shape skeletonization[10], 3D shape recovering[11] and motion tracking[12].

The paper also presents a new model improving the deformable contour algorithm detecting the contour by incorporating a prior knowledge about the shape and variability of objects to be extracted in detection process[3-4]. In the model, the contour in the image is represented by a set of labeled radial distance vectors, each of which is radiated from a fixed point on the core, called *anchor point*. The deformable contour model is modeled as an elastical body subject to the continuum mechanical laws. When the contour model is initially placed near image features, it is deformed by varying the magnitude of the radial distance vectors subject to two types of force, intrinsic force and extrinsic force. The proposed deformable contour model has features that can solve most problems encountered with the existing snake models, while preserving most of their attractive points. Control points on the contour are no longer bunched together in parts of the contour where remarkably dominant features appear. Another advantage is that the computational time for the operation of the proposed contour model decreases considerably in comparison with existing snake models. Finally, appropriate level of prior knowledge about the shape and its variability of the object to be extracted can be easily involved for each of particular applications. This feature significantly improves the detection performance under varying conditions.

2. Brief Review of The Snake Models

The snake contour model, originally proposed by Kass *et al.*[9], is a controlled continuity spline represented by a set of point vectors, $v(s) = (x(s), y(s))$, having the arc length S as a parameter. In their work, they defined an energy functional of the contour model and described a method for finding contours which correspond to local minima of the functional. The energy functional is written as

$$E_{snake} = \int_0^1 [E_{int}(v(s)) + E_{image}(v(s)) + E_{con}(v(s))]ds \qquad (1)$$

where E_{int} represents the internal energy of the contour due to the discontinuity or bending. E_{image} gives rise to the image forces which push the contour toward dominant image features, and E_{con} is the external constraints, which are intended for putting the contour at specified positions on the image plane. The internal spline energy introduced by Kass *et al.* is written as

$$E_{int} = (\alpha(s)|v_s(s)|^2 + \beta(s)|v_{ss}(s)|^2) / 2 \qquad (2)$$

The spline contour energy is composed of the first-order term controlled by $\alpha(s)$ and the second-order term controlled by $\beta(s)$, in which the $\alpha(s)$ and $\beta(s)$ are weighting factors. The first-order term makes the contour behave like a membrane, and the second-order term makes it act like a thin plate. That is, the values of $\alpha(s)$ and $\beta(s)$ at a point determine the extent to which the contour is allowed to stretch or bend at that point. The relative size of $\alpha(s)$ and $\beta(s)$ can be chosen to control the influence of the corresponding constraints. The minimum energy contour is determined using variational calculus. Using the snake models has proved to be a very attractive and efficient method, but it still encounters several problems, some of which have been pointed out by Amini *et al.*[10]. First, the contour shrinks due to the effect of internal energy when it is not subject to any external forces, and, consequently, it finds its own equilibrium at a point or a line. Secondly, control points on the contour can navigate along the contour as well as along the direction perpendicular to it, and, thereby, the points tend to be bunched together in parts of the contour where the image forces are higher. Thirdly, the results obtained by the snake model are considerably sensitive to the selection of the parameters associated with the model as well as the initial position of the contour. Distinctly different results can be produced on the same image data by slightly different parameters and initial positions. The other critical disadvantage of the snake models is that they do not utilize the prior knowledge about overall shape and its variability of the contour to be extracted, which often play an important role in improving the detection performance in the presence of some disturbing image features. The new contour model proposed in this study is attempted to solve most problems encountered with the original snake models.

3. Proposed Elastic Contour Model

In this section, a new active method for locating the target objects in images is described that is mainly conceptualized by a elastic contour model. The proposed model simulates an elastic body where elastically deformable part surrounds a rigid core (or spine) with fixed shape. In contrast to the snake models, the main feature of this model is the use of the prior knowledge about overall shape and shape variability of the object to be extracted.

3.1 Shape Representation

In order to represent a contour(or curve if not closed), a set of discrete points, $P = \{p_i | 1 \le i \le N\}$, are chosen to be evenly spaced on boundaries of the object. Then, the shape of a contour can be specifically described by a set of radial distance vectors based on a modified polar-coordinates where a set of anchor points on a core replace a reference point in the original polar-coordinates. Given a core, the shape of the contour can be represented by an one-dimensional radial distance vector distribution S:

$$S = \{ \mathbf{r}_i \mid 1 \le i \le N \} \qquad (3)$$

where $\mathbf{r}_i = p_i - q_i$ is the relative vector of the i^{th} control point p_i on the contour with respect to the i^{th} anchor point q_i on the core (see Fig.1 for the illustrative definitions). A set of the anchor points, $Q = \{q_i | 1 \le i \le N\}$, are normally chosen to be evenly spaced on the core surface, in which the core is non-pliable or rigid body forming the basis of shape of a deformable contour like the spine of a vertebrate. In this representation, the changes in the radial distances are no other than the change in shape of the contour. This shape representation considerably facilitates the development of our improved active contour model introduced in the followings.

3.2 Elastic Model

Basically, a contour in the proposed elastic model behaves just like the elastic bodies obeying the classical mechanical laws that the contour is deformed by varying the radial distance vector distribution. Fig.2 makes the elastically deformable contour model comprehensive. The articulated elastic rods are supposed to move frictionless along a fixed linear track . This contour model means that it never resists against its own stretching but resists against only its bending. If a rod is subject to some external forces, deformation occurs in accordance with the mechanical properties of the rods. When the rigidity of each rod is relatively small, large deformation will occur only at the local part of the contour. On the contrary, sufficiently large rigidity will cause a small but uniform amount of deformation over the wide region of the contour.

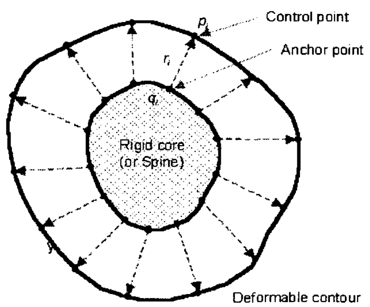


Fig.1. Contour representation in the proposed model

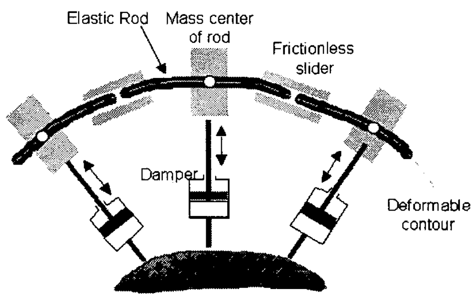


Fig.2. Contour representation in the proposed model

(1) Intrinsic Force Models

In order to establish a concrete foundation for the elastic model, two classes of rigidity are defined: the first-order rigidity and the second-order rigidity. The first-order rigidity encodes a measure of resistance to deformation of the contour from its home shape, while the second-order rigidity encodes a measure of tendency to smooth any deformation from the home shape. The home shape here is characterized by shape of the core. These rigidity terms can be materialized by the internal springs arranged so that the motions of neighboring particles interact with each other. The elastic contour model with the first-order rigidity term can be represented by a mechanical system as shown in Fig.3(a), in which the first-order rigidity terms are expressed by the internal springs, indicated by α, interconnecting between two neighboring particles. The internal springs here are arranged so as to be unforced when the radial displacements of the two neighboring particles are equal to each other. When external force $f_{ext,i}$ is submitted to the i^{th} particle with mass m_i of this elastic system, the distance r_i between the i^{th} particle and the i^{th} anchor point is changed in accordance with the following dynamics:

$$m_i \ddot{r}_i + c_i \dot{r}_i + f^{\alpha}_{int,i} = f_{ext,i}$$
$$f^{\alpha}_{int,i} = \alpha_i (r_i - r_{i-1}) + \alpha_{i+1} (r_i - r_{i+1}) \qquad (4)$$

where c_i is the damping coefficient attached to the i^{th} particle, and $f^{\alpha}_{int,i}$ is the internal force reacted by the springs α when the relative motions between the i^{th} particle and its two neighboring particles occur. The inertial force is generated by the motion of the particle with mass m_i as it evolves with time. The damping term is added to avoid the cases in which the contour oscillates around an equilibrium position.

Fig.3(b) shows another class of the elastic contour model with the second-order rigidity, in which the internal force $f^{\beta}_{int,i}$ exerted by the second-order rigidity on the i^{th} particle is written as

$$f^{\beta}_{int,i} = \beta_{i-1}(r_{i-2} - 2r_{i-1} + r_i) - 2\beta_i(r_{i-1} - 2r_i + r_{i+1}) + \beta_{i+1}(r_i - 2r_{i+1} + r_{i+2}) \qquad (5)$$

where β is a coefficient for the internal springs interconnecting among three neighboring particles. This is so arranged that the springs are unforced when the radial displacement of the mid particle is equal to the average of the other two particles. Fig.4 illustrates the role of the rigidity terms in the contour model.

Let the total internal force of the contour model due to the first and second order rigidity terms $f_{int} = f^{\alpha}_{int} + f^{\beta}_{int}$. When the i^{th} particle is subject to an external force $f_{ext,i}$, the total motion of the particle m_i is then governed by the following dynamic equation:

$$m_i \ddot{r}_i + c_i \dot{r}_i + f_{int,i} = f_{ext,i} \qquad (6)$$

where three of the left terms correspond to intrinsic forces in the elastic contour model.

(2) *Extrinsic Force Model*

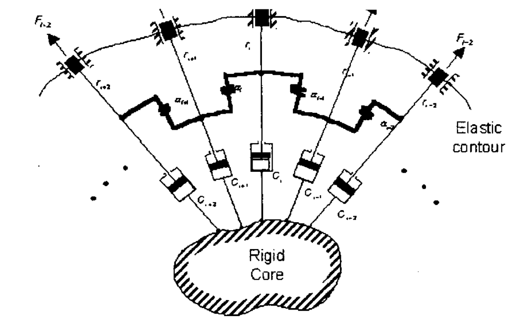
The extrinsic force f_{ext} is externally caused from image features such as edges and lines. Finding such image features in an image can be done with very simple methods; calculating the image gradient for edges and using the image intensity for lines. Let the potential energy (or magnitude) of edge feature and line feature be P_{edge} and P_{line}, respectively, then they can be written as

$$P_{edge} = |\nabla(G_s * I(x,y))|^2$$
$$P_{line} = G_{\sigma} * I(x,y) \qquad (7)$$

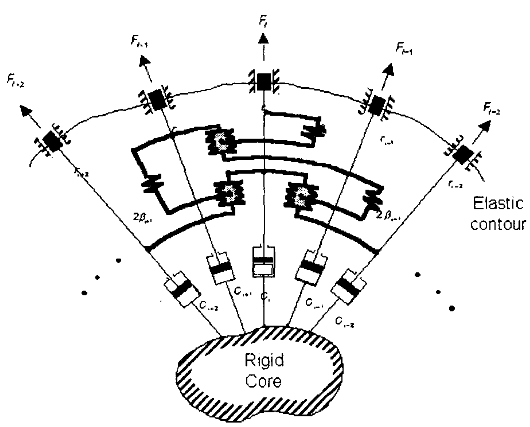
where $\nabla = (\frac{\partial}{\partial x}, \frac{\partial}{\partial y})$. In this equation, $I(x,y)$ is the image intensity at the image coordinate (x,y) of a particle, and G_σ is a Gaussian of standard deviation σ. The total image potential energy can be expressed as a weighted combination of the two potential energies:

$$P_{total} = w_{edge} P_{edge} + w_{line} P_{line} \quad (8)$$

where w_{edge} and w_{line} are the weighting factors indicating the influence of each potential energy term to the total image potential energy.



(a) Elastic contour with the first-order rigidity



(b) Elastic contour with the second-order rigidity

Fig.3. Elastic contour model with the rigidity

The external force is made to generate the force which can attract a particle to the position possessing the maximum image potential energy. Therefore, the external force can be defined so that it is created in proportion to the gradient of the total image potential energy in the direction of the radial distance vector. The external force f_{ext} then is obtained by

$$f_{ext} = \nabla_r P_{total} \quad (9)$$

where $\nabla_r = \frac{\partial}{\partial r}$. In this equation, r is the radial distance vector.

3.3 Numerical Solution

In order to solve the equation(6) computationally, the first and second-order derivatives in time are approximated by using the finite difference method.

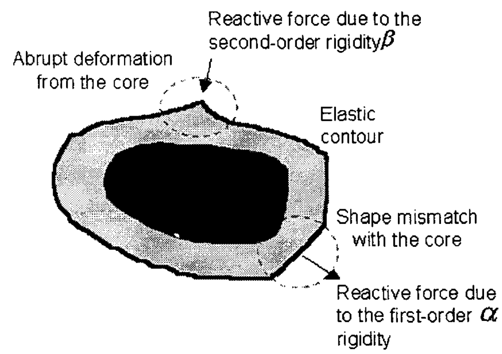


Fig.4. Effects of the rigidities in the contour model

Let us suppose that the mass and viscous coefficients of all particles are equal, $m_i = m$ and $c_i = c$, respectively. Then, this assumption results in a set of N linear equations, which can be written in the following matrix form:

$$R(t) = D^{-1} B(t-1, t-2) \quad (10)$$

where t is the time step and the following identities are used:

$$D = \left[\left(\frac{c}{2} + m\right) I\right] + A \quad (11)$$

$$B(t-1, t-2) = F_{ext}(t-1) + 2mR(t-1) + (\frac{c}{2} - m)R(t-2)$$

In the above equations, $R(t) = (r_1(t), r_2(t), \cdots r_N(t))^T$ are the radial distance vectors at the time t, $F_{ext}(t) = (f_{ext,1}(t), f_{ext,2}(t), \cdots f_{ext,N}(t))^T$ are the external forces, I denotes the identity matrix, and the matrix A represents all internal elastic relations of the contour model. The matrices D and A possess the properties of being *symmetric* and *penta-diagonal*. The elastic contour model can be also considered as a static mechanical system, in which massless particles are only considered by eliminating all of the viscous dampers from the dynamic contour model. This system reaches the equilibrium only if the external force is equal to the internal force. For a contour consisting of N control points, this can be written in the following matrix form:

$$A R(t) - F_{ext}(t) = 0 \quad (12)$$

for the term R and an explicit scheme for the term F_{ext}. The result is obtained by

$$R(t) = D^{-1}B(t-1) \quad (13)$$

where the following identities are used:

$$D = \tau I + A$$
$$B(t-1) = F_{ext}(t-1) + R(t-1). \quad (14)$$

Here, τ is a step size which controls the convergence characteristics of the solutions with respect to time for the dynamic model of the mass m and viscous coefficient c.

4. EXPERIMENTS AND DISCUSSIONS

In order to demonstrate the performance and some of the characteristics of the proposed approach, a series of experiments were conducted. The experimental system used in this approach is composed of three units: a CCD camera, a personal computer system and an image processing system. In this system, the image processing system, *AIS-4000* of *Applied Intelligent Systems Inc.* samples the video signal from the CCD camera into *512(H) x 256(V)* pixels, and digitizes it into 256 gray levels. The algorithms were implemented by using an object-oriented programming language(*Intelligent C*) on IBM PC, and then were downloaded into the image processor. For the simplicity, contour models in the experiments were regarded as static systems, which motion are governed by the equation(13). The core was interactively built so that its shape may resemble the expected shape of the contour to be extracted. The parameters must be also appropriately set to apply the equation of motion.

4.1. Tracking of Moving Objects

The experiments were conducted on several different images, each of which was carefully selected to demonstrate several distinct features of the proposed contour model. The proposed contour models do good job for tracking objects undergoing rigid or non-rigid motion. Fig.5 shows the results of tracking boundaries of a human hand undergoing non-rigid motion. The motion of fingertips shown in Fig.5 occurred in regular sequence from (a) to (d), in which each frame was selected out of a two-second video sequence. The automatic tracking starts with manual initialization of edge-attracted contour model on the main boundary of the target object in each of the first frames. To prevent the unnecessary large deformation of the contour due to translational motion of the object, at given interval in the iteration process, the center of the core was shifted to be the centroid of the contour. In the experiment, the shape of the core was changed to the shape of the contour to allow large deformation of the contour over a long time.

4.2 Detection of Open Curve

The proposed deformable contour model can detect open curves as well as closed contours, while the original snake models are usually likely to fail in detecting open curves due to the smoothness violation between two ending points of the contour. Fig.6 shows the results of tracking a deformable wire by using the proposed method, in which the consecutive frames from (a) to (d) were selected out of a two-second video sequence. In the figures, short vertical lines indicate the trajectories along which the control points on the contour model move from the previous frame to the current frame.

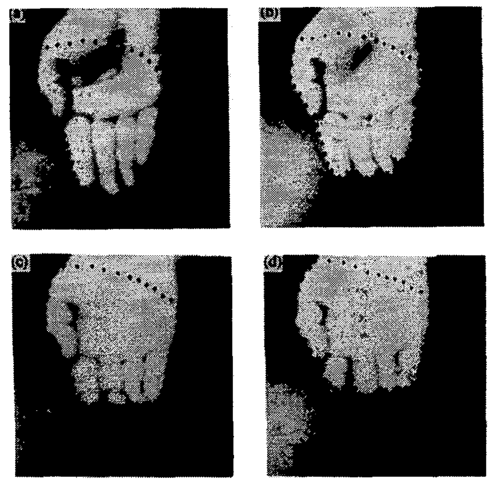


Fig. 5 Results of tracking boundary of the human hands undrgoing non-rigid mtion from (a) to (d).

The contour here was attracted by line features defined as the maximum brightness. For the tracking motion between two successive frames, the contour at steady state of the previous frame serves as the initial contour for the current frame. In these experiments, the core is simply made to be a horizontal line in the image plane. Therefore, the smoothness between the radial displacement of the leftmost control point and that of the rightmost one can be conserved even though a relatively large deformation occurs between the two end points. This feature significantly improves the detection performance of an open curve, as demonstrated in these experiments.

4.3 Comparison with Original Snake Model

For the comparison with the original snake model[9], the iteration characteristics of the proposed contour model are depicted in Figs.8(a) and (b), each of which was resulted from the circle images with initial contours superposed as shown in Figs.7(a) and (b), respectively. When the initial contour was placed in the outside of circle, the convergence characteristic of the proposed contour appears to be relatively similar to that of the snake models. On the contrary, when the contour was initialized in the inside of circle, it can be shown that distinctly different results were obtained. In comparison with the proposed model, the original snake model shows much slower convergence rate, and even steady state error from the desired solution. The results show that the proposed method yielded the good detection results of the main boundary regardless of the location of the initial contour. One of the most authentic causes of above results is the fact that the snake model tends to contract on itself in parts where no or relatively weak external forces are exerted. This feature of the snake model often leads the contour incorrectly to points of some unexpected image features in the inside of the expected boundary to be extracted. In comparison with the snake model, the proposed contour model appears to be robust against such unexpected image features around the boundary to be extracted since it tends to keep its home shape.

5. Concluding Remarks

In this study, a new active contour model was presented to improve the performance of detecting 2-D contours in images. The proposed active model was attempted to overcome several existing problems with the snake algorithms that are difficult to use the prior knowledge about the expected shape and its variability of the contour to be extracted. In the model, a deformable contour in image is represented by a set of radial distance vectors radiating from a core, which resembles the shape of the contour to be extracted. The proposed elastic contour model is derived through dynamic or static analyses of a virtual elastic mechanism, where the contour deforms by varying the radial distance vectors distribution according to the continuum mechanical laws. The contour tends to keep its home shape and smooth the deformation when a deformation from its home shape occurs due to significant external forces. The performance of the proposed elastic contour model was validated through a series of experiments which covered tracking object under non-rigid motion, detection of a open curve and comparison of convergence with other snake models.

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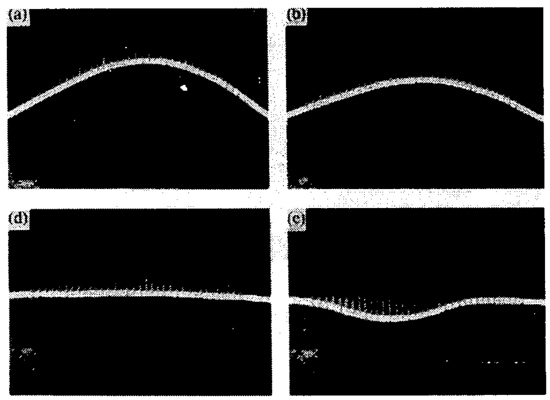

Fig.6 Results obtained by applying the proposed contour model to a flexible wire with deformatiotion (a)~(d)

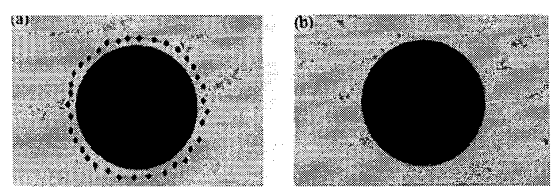

Fig.7 The test images. (a) Initial contour placed in the outfside of the object (b) initial contour placed in the inside of the object.

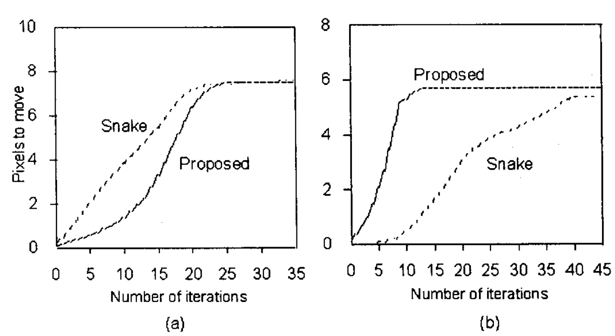

Fig.8 Comparison of the iteration characteristics of the proposed model with the snake model