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DEFORMABLE OBJECT TRACKING USING ACTIVE CONTOUR MODEL

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Abstract: An active contour model is proposed for the problem of image segmentation. It has been applied to the tracking of deformable moving objects in the 2D image plane. For the edge detection of images, its energy function is defined and the object contour is recognized by minimization of the energy function. The active contour model is a useful method for tracking deformable objects, but it uses the energy function that is sensitive to the initialization of active contour. It is therefore hard to converge to a deep concave shape. Moreover, it is easy to detect a wrong contour by converging to the local minimum. Thus, in this paper, a new energy function which can overcome these weak points is proposed and it is applied to the tracking of moving objects. Experiments were carried out with the proposed method and the effectiveness of the new energy function was verified. *Copyright 2002 IFAC*

Keywords: Active Contour Model, Computer Vision, Tracking, Image Segmentation

1. INTRODUCTION

The active contour model has been successfully applied to computer vision and image analysis such as the detection of an edge, since it was proposed (Kass, *et al* 1987). In general, the active contour model is represented with energy functions, and the contour of objects is recognized by minimization of the energy functions. The energy function of the active contour model basically consists of internal, external, and image energy terms which are based on the integration of prior knowledge based on the location, shape, and size of the desired object. Each term of energy functions is represented by a set of nodes which lie on an edge. Each node of the active contour can find the contour of objects successfully through the energy minimization process, and a new contour can be searched for in the two more sequential images. Therefore, we can treat the problem of image segmentation as the problem of tracking objects for the active contour model (Lam, 1998). However, the active contour model has weak points. For example, it is sensitive to the initialization of the active contour (William, 1991), and the minimization of the energy function depends on the shape of objects (Kim, *et al* 1999). Thus, in this paper, the modified energy function to overcome these weak points is proposed and it is applied to tracking of moving objects

2. THE ACTIVE CONTOUR MODEL

2.1 *The general energy function*

An active contour model is represented by a vector, $v(s) = (x(s), y(s))$ having the arc length, s, as a parameter. An energy functional for the contour is defined by

$$\int E_{snake}(v(s))ds = \int E_{int}(v(s))ds + \int E_{ext}(v(s))ds + \int E_{image}(v(s))ds \quad (1)$$

where E_{int} represents the internal energy of the contour due to bending or discontinuities, E_{ext} is the external energy inflicted through user interface, and E_{image} is the image energy which is composed of line, edge and termination terms. The internal energy consists of the first order differential term $v_s(s)(= dv/ds)$ controlled by and the second order differential term $v_{ss}(s)(= d^2v/ds^2)$ controlled by as follows (William, 1991) :

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

The internal energy function is intended to enforce a shape on the deformable contour and to maintain a constant distance between nodes in the contour. Therefore, the first order continuity term acts like a membrane and the second order curvature term causes an active contour to grow or shrink. Thus, in the absence of other influences, which means that $\beta(s)$ is 0, the continuity energy term coerces an open deformable contour into a straight line and a closed deformable contour into a circle. Additionally, the curvature term can be used on a closed deformable contour, which means $\alpha(s)$ is 0, to force the contour to expand or shrink in the absence of external influences (Cohen, 1991; Gunn, 1994). Fig. 1 shows the interpolation by the internal energy.

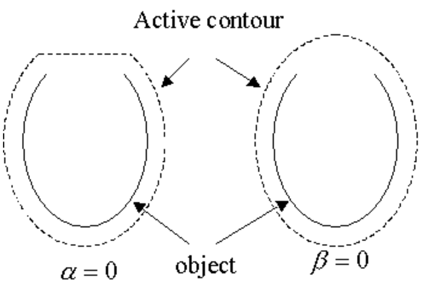


Fig. 1. Interpolation by the internal energy

Fig.2 shows the direction of minimization for each node of the active contour, when only the internal energy is concerned. In Fig.2, v_{i-1}, v_i and v_{i+1} represent nodes of the active contour and $\bar{u}_i$ and $\bar{u}_{i+1}$ are the vectors occurring from $v_i - v_{i-1}$ and $v_{i+1} - v_i$, respectively (Kim, *et al* 1999).

During the minimization using the only internal energy function, each node of the active contour moves along the vector $\bar{u}_{i+1} - \bar{u}_i$. The magnitude of the minimization vector depends on the value of the curvature (Kim, *et al* 1999). In order to compare the values of the curvature about each position, we are concerned with the three nodes shown in Fig. 3. Table 1 shows the values of curvature according to the calculation method (William, 1991). As shown in Table 1, when the three nodes are horizontal $a - b - c_1$, the value of curvature is at a minimum. Therefore, we can

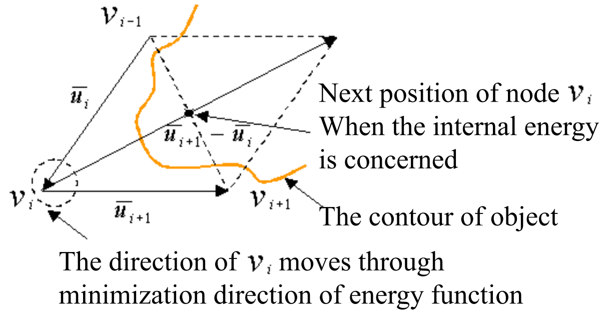


Fig. 2. Direction of minimization

guess the movement of node v_i like in Fig. 2. Consequently, in the case when the object has a deep concave shape, it is hard to shrink into the center of objects with only internal energy.

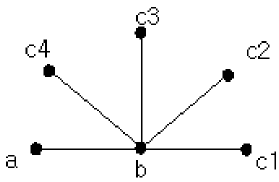


Fig. 3. Arrangement of nodes a, b and c

Table 1. Comparison of values of curvature according to calculation methods.

Type	$(d\theta/ds)^2$	$\|v_{ss}\|^2$	$\|\bar{u}_i - \bar{u}_{i+1}\|^2$
$a - b - c_1$	0.00	0.00	0.00
$a - b - c_2$	0.42	0.40	1.00
$a - b - c_3$	0.47	2.00	2.00
$a - b - c_4$	3.80	2.34	5.00

2.2 *Minimization of the active contour model*

The active contour model detects the edge of objects through the minimization of the energy function. The final active contour, which will be a contour of the object, depends, however, on its initial position. Thus, we present four types of the initialization of active contour for the closed contour shown in Fig. 4. In Fig. 4, a) is outside, b) is overlap, c) is inside, and d) is perpendicular. The type d) is easy to converge to the local minimum and hard to acquire the proper edge of objects. However, the other types are proper for the initialization of the active contour model (Kass *et al* 1987). In this paper, for the minimization of the active contour model, the greedy algorithm (William, 1991) is used. The greedy algorithm is faster than dynamic programming and more stable and flexible than the variational calculus approach of Kass. In general, the greedy algorithm selects a searching window for each node shown in Fig. 5. The energy function is computed for the current location of v_i and each of its neighbors. The location having the smallest value is chosen as the new position. This process is performed repeatedly until the global minimum is found.

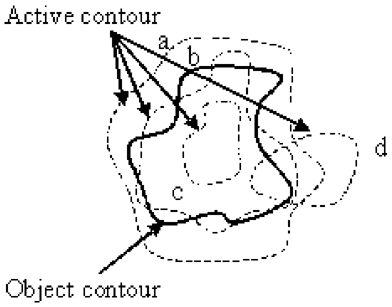


Fig. 4. Initialization for the active contour

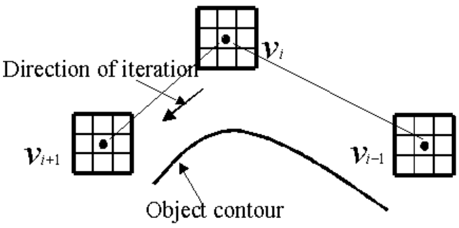


Fig. 5. The energy function is computed at v_i and each of its eight neighbors. The location having the smallest value is chosen as the new position of each node

3. PROPOSED ACTIVE CONTOUR MODEL

The internal energy function is intended to enforce a shape on the deformable contour and maintain a constant distance between nodes in the contour preventing the active contour from shrinking into a deep concave shape. Therefore, the energy function should be modified to overcome the weak point of it. Additionally, applied to tracking objects, the energy function also modified in order to refer to the position information of nodes in the previous frame. In the case of the continuity term, there is a modification to keep even distance between nodes as in the normal active contour model. The curvature term is changed to take the role of nodes of the active contour detecting the variation of contour. Therefore, the continuity term is modified as follows :

$$E_{cont} = \alpha_i |u_i^t - u_i^{t-1}| \tag{3}$$

where u_i^t is $v_i^t - v_i^{t-1}$ and u_i^{t-1} is $v_i^{t-1} - v_{i-1}^{t-1}$ the superscript $'t'$ is the current frame and the superscript $'t-1'$ is the prior frame and α_i is the weighing value for the continuity term. The curvature term is modified as follows:

$$E_{cur} = \beta_i |E_{curi}^t - E_{curi}^{t-1}| \tag{4}$$

where

$$E_{curi}^t = |v_{i-1}^{t-1} - 2v_i^t + v_{i+1}^{t-1}|^2 \tag{5}$$

$$E_{curi}^{t-1} = |v_{i-1}^{t-1} - 2v_i^{t-1} + v_{i+1}^{t-1}|^2 \tag{6}$$

E_{curi}^{t-1} and E_{curi}^t are curvature energies in the prior and current frame respectively. v_i^t is the candidate position for the next location of nodes during minimization. β_i is the weighing value for the curvature term. In order to overcome the weak shrinkage force for objects with deep concave shapes, a new energy term for the internal energy is suggested as follows :

$$E_{cont} = \gamma_i |v_i - G| \tag{7}$$

where $G$is the center point of the active contour and γ_i is the weight value for the added term. Its term is the magnitude of the vector from the nodes to G. Therefore, this term helps each of the nodes to move into the deep concave part of objects. Fig. 6 shows the center point of snakes and vectors for the closed contour.

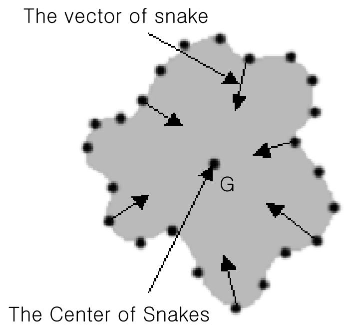


Fig. 6. The center of snakes and vector

Finally, the internal energy function is proposed as follows :

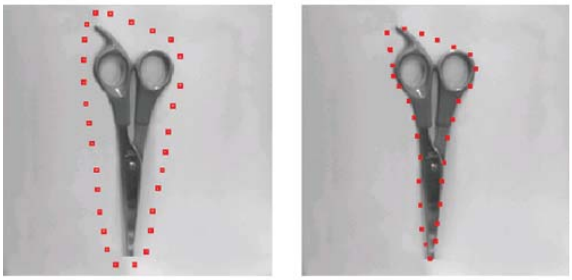
$$E_{int} = \alpha_i |u_i^t - u_i^{t-1}| + \beta_i |E_{curi}^t - E_{curi}^{t-1}| + \gamma_i |v_i - G| \tag{8}$$

4. EXPERIMENTAL RESULTS

In order to demonstrate the performance of the proposed energy function, experimental results for still images and for the sequential images are given. In both experiments, 256*256 gray level images and 320*240 gray level images were used respectively. A PIII 500MHz processor is used for the image processing.

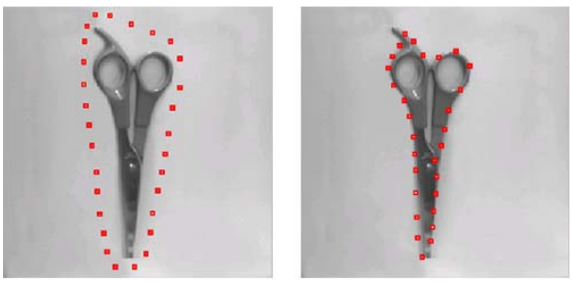
4.1 *Performance of the proposed energy function for still images*

In still images, the proposed energy function and the normal energy function which is proposed by Williams are compared for an object with a concave shape. The quantity of snake node is decided by the shape of object, and the number of iteration is concerned with the distance of initial position of snakes. The weighting values, α, β and γ are used 1, 1 and 1.2 respectively. In Fig. 7, 8, scissors is used for experiments. In Fig. 7, The normal energy function is used for edge detection. As result in Fig. 7, the upper edge of scissors cannot be detected. But the edge detection using the proposed energy function gives better results for the same object that is shown in Fig. 8. Also, Fig. 9 shows the minimization of energy function for iteration. As result, proposed energy function is faster than normal energy function for converging, even though the initial value of proposed energy function is large. In Figs. 10 and 11, the results of different objects with the concave shape are shown.



a) Initial position of snakes b) Final position of snakes

Fig. 7. Result of edge detection using the normal energy function



a) Initial position of snakes b) Final position of snakes

Fig. 8. Result of edge detection using the proposed energy function

4.2 *Tracking of moving objects*

In the experiments of this study, the proposed energy function is used for tracking an object. The experimental results are obtained by using the image grab board which can acquire about 12 frames per second. Fig. 12 shows that a human hand was selected as a deformable object for tracking. For tracking an human hand, 20 nodes are used. As result, the active contour settled around the edge of the changing hand for 5 seconds. In Fig. 13 shows that the nodes escaping from the local minimum by resetting of the initial active contour during tracking an object. As shown Fig. 13(a), the nodes cannot recognize the object, because of converging to the local minimum. However, resetting of active contour can help escaping from local minimum of active contour as Fig. 13(b). Finally, we measure the position of an object, which is put on the bed moving forward and backward repeatedly, using

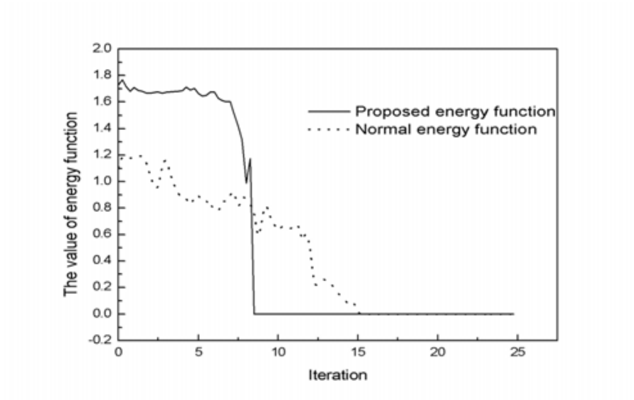
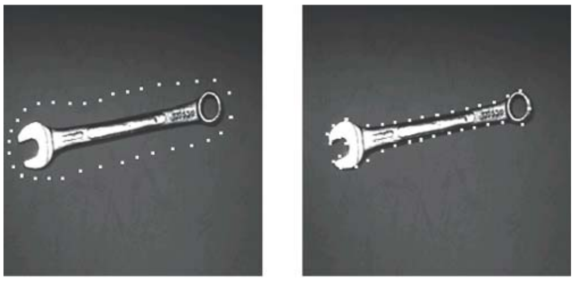
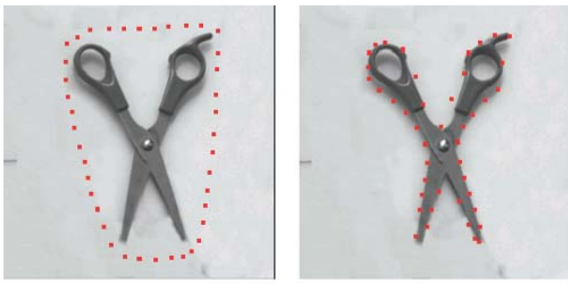


Fig. 9. Compared with the value of an energy function



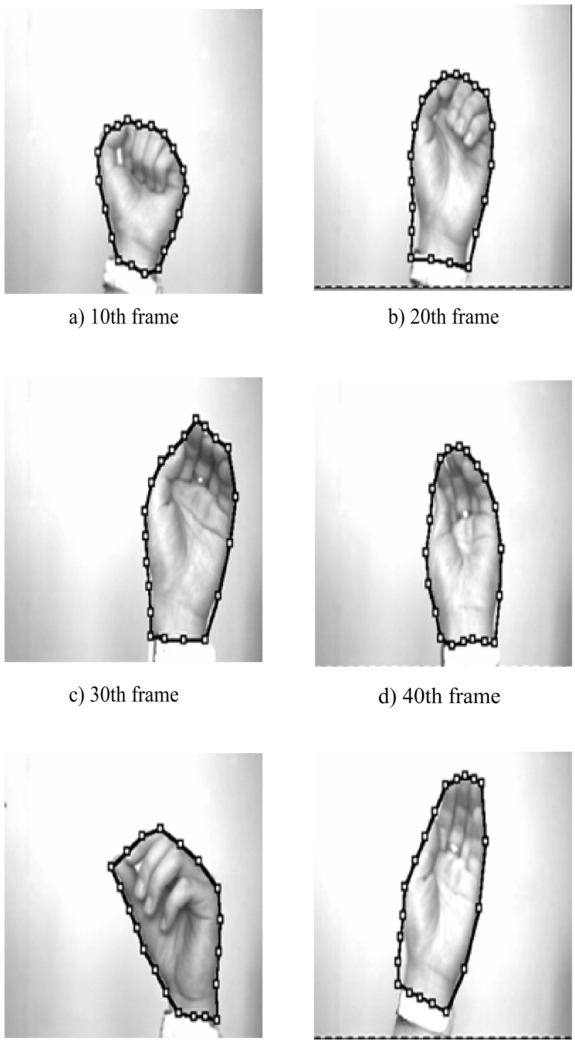
a) Initial position of snakes b) Final position of snakes

Fig. 10. Edge detection for a spanner



a) Initial position of snakes b) Final position of snakes

Fig. 11. Edge detection for scissors



a) 10th frame

b) 20th frame

c) 30th frame

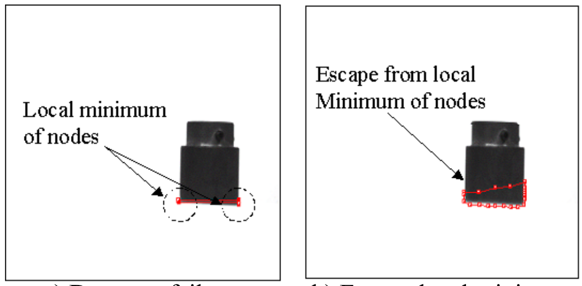
d) 40th frame

e) 50th frame

f) 60th frame

Fig. 12. Tracking results for a hand

the proposed energy function. Fig. 14 shows the experimental layout, and on the assumption that a camera is parallel to the object. A sinusoidal signal is exited to the DC motor installed in the bed, and the images are acquired about 12frames per a second. Figs. 15 and 16 show experimental results of the edge detection and the position measures for a moving object, respectively. In Fig. 16, the dotted line represents the positions obtained through the encoder, and the solid line represents calculations from the vision system using the proposed energy function. Results show that the edge of the moving object is nicely detected, and the object positions are measured with satisfaction. However, during the first period in motion, the proposed energy function cannot detect the exact position due to calculating the maximum length of the moving field. After the first period, however, we can obtain the position information from vision data.



a) Detect to fail

b) Escape local minimum

Fig. 13. Escape from the local minimum by resetting the active contour

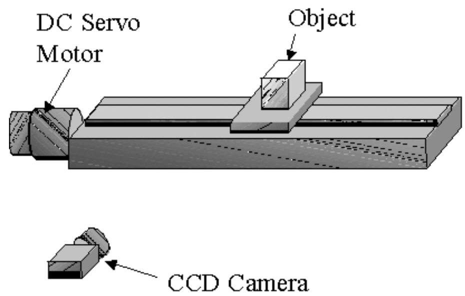
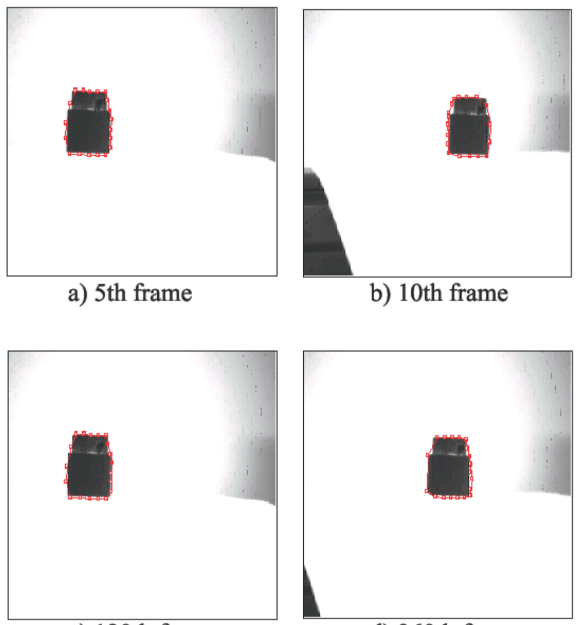


Fig. 14. Layout for the experiment



a) 5th frame

b) 10th frame

c) 120th frame

d) 360th frame

Fig. 15. Tracking of an object moving forward and backward repeatedly

5. CONCLUSIONS

In this paper, we discussed the problems of the active contour model for computer vision and image analysis. In order to overcome the problems of active contour model, a modified energy function is suggested. The proposed energy function is applied to the still image and tracking of a moving object. we can get excellent results through the experiments. In the case of tracking an object, we

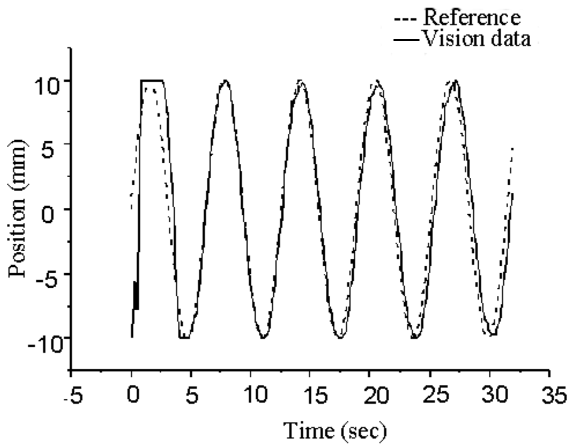


Fig. 16. The position of an object

could detect the position of a moving object with image segmentation. As the results of experiment, the proposed energy function is more effective to image segmentation without regarding to the shape of objects. Although there was a time-delay in measuring the position of moving an object due to the low performance of the image board, the image segmenting and the measuring of position could be obtained simultaneously.

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