Modified energy function of the active contour model for the tracking of deformable objects

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An active contour model has been used to detect the edges in a still image. In order to apply the active contour model to edge detection, the energy function which consists of internal, external and image energies should be defined. After defining the energy function, the edge of an object is detected through minimization of the value of the energy function. In this paper, the modified internal energy function is proposed to improve the convergence of the energy function when the active contour model is applied to the tracking of deformable objects using the greedy algorithm. In order to show the performance of the proposed energy function, experiments were carried out for the still and animated images..

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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[1]. In general, the active contour model is represented with energy functions, and the contour of objects is detected 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 such as the location, shape, and size of the desired object. Each term of the 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. In the previous work[2], however, the direction of convergence of energy value was not optimized to detect an edge of an object. Therefore, the improved internal energy function was proposed for compensation. The proposed energy function improves the performance of edge detection. Moreover, the internal energy function was modified for detecting edge of a moving object. At this time, the frame information is involved in the internal energy function. The performance of the proposed energy function is evaluated by comparing with the results using the general energy function.

2. The active contour model

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

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

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 $\alpha(s)$ and the second order differential term $v_{ss}(s)$ ($=d^2v/ds^2$) controlled by $\beta(s)$ as follows[2]:

$$E_{\text{int}} = \alpha(s)\,|\,v_s(s)\,|^2 + \beta(s)\,|\,v(s)_{ss}\,|^2 \quad (2)$$

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, i.e. $\beta(s)$ 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, i.e. $\alpha(s)$ is 0, to force the contour to expand or shrink in the absence of external influences[3].

Fig. 1 shows the influence of the internal energy function mentioned above. 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 u_i

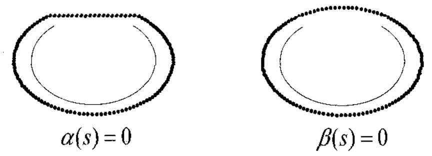


Fig. 1 Interpolation by the internal energy

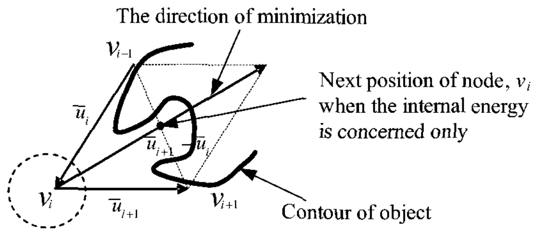


Fig. 2 Direction of minimization

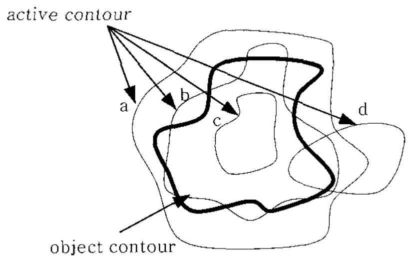


Fig. 4 Initialization for the active contour

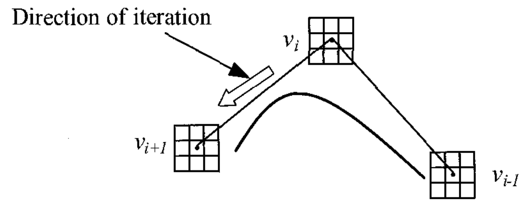


Fig. 5 The energy function computed at v_i and each of its eight neighbors

and u_{i+1} are the vectors occurred from $v_i - v_{i-1}$ and $v_{i+1} - v_i$, respectively[4].

During the minimization using the only internal energy function, each node of the active contour moves along the vector $u_{i+1} - u_i$. The magnitude of the minimization vector depends on the value of the curvature. In order to compare the values of the curvature about three points of active contour model, specific positions of the nodes for the active contour model are concerned with the three nodes shown in Fig. 3. In the figure, the position of a and b are fixed and c is changed c_1, c_2, c_3, c_4 and c_5. Table 1 shows the values of curvature according to the calculation method[2]. As shown in Table 1, when the three nodes are horizontal $a-b-c_1$, the value of curvature is at a minimum. Therefore, one can guess the movement of node v_i like in Fig. 2.

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[1].

In this paper, for the minimization of the active contour model, the greedy algorithm is used[2]. 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 as shown in Fig. 5. The energy function is calculated for the current location of v_i and each of its neighbors. The location having the smallest value is chosen as the new position.

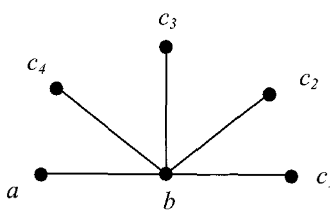


Fig. 3 Arrangement of nodes a, b and c

3. Proposed active contour model

The internal energy function of the general active contour model does not provide information of image for each frame. In order to apply it to the tracking objects in animated image, the energy function is also modified referring to the position information of nodes in the previous frame. Therefore, the modified internal energy function is proposed in this paper. 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:

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

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, the superscript '$t-1$' is the prior frame, and α_i is the weighting value for the continuity term. The curvature term is modified as follows:

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

where

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

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

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. $\beta(s)$ is the weighing value for the curvature term.

In order to reduce the time of the convergence a new energy term for the internal energy is suggested as follows:

$$E_{add} = \gamma_i \left| v_i - G_j \right| \tag{5}$$

where G_j is the center point of a partial block of the active contour, and γ_i is the weight value for the added term. Its value is the magnitude of the vector from the nodes which belong to a partial block of the active contour to G_j. Therefore, this term helps each of the nodes to move into the deep concave part of objects. Fig. 6 shows partial blocks and vectors for the closed contour. Finally, the internal energy function is proposed as follows:

$$E_{proposed} = \alpha_i \left| u_i^t - u_i^{t-1} \right| + \beta_i \left| E_{curi}^t - E_{curi}^{t-1} \right| + \gamma_i \left| v_i - G_j \right| \tag{6}$$

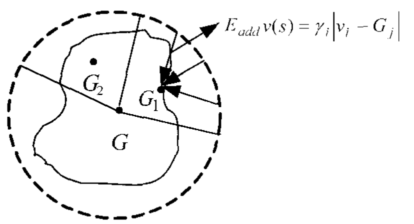
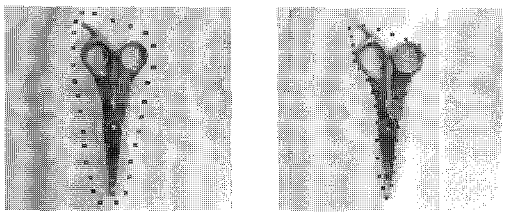


Fig. 6 Partial blocks and added energy function

The proposed internal energy function for tracking an object is modified based on general active contour model, and the each node of the active contour was constructed to share the information of the image of the previous frame.

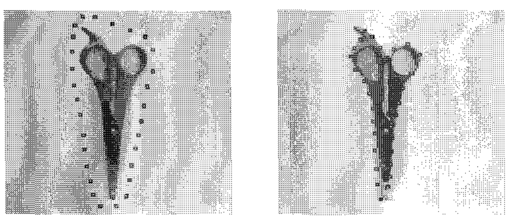
4. Experimental results

For the still images, the proposed energy function and the normal energy function were compared. As shown in Fig. 7, some nodes could not converge to the upper edge with a concave shape. The edge detection using the proposed energy function gave better results for the same object that is shown in Fig. 8. Also, in Figs. 9 and 10, the results of different objects with the concave shape are shown. In the experiments for tracking an object, the experimental results were obtained by using the image grab board which could acquire about 12 frames per second.



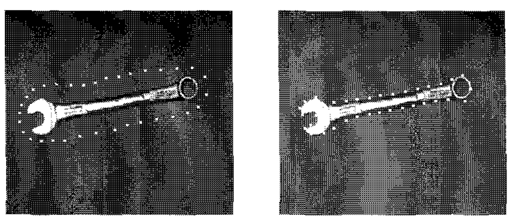
a) Initial contour b)Result image

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



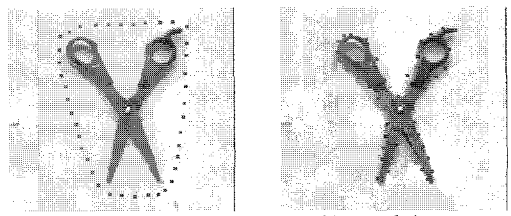
a) Initial contour b) Result image

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



a) Initial contour b) Result image

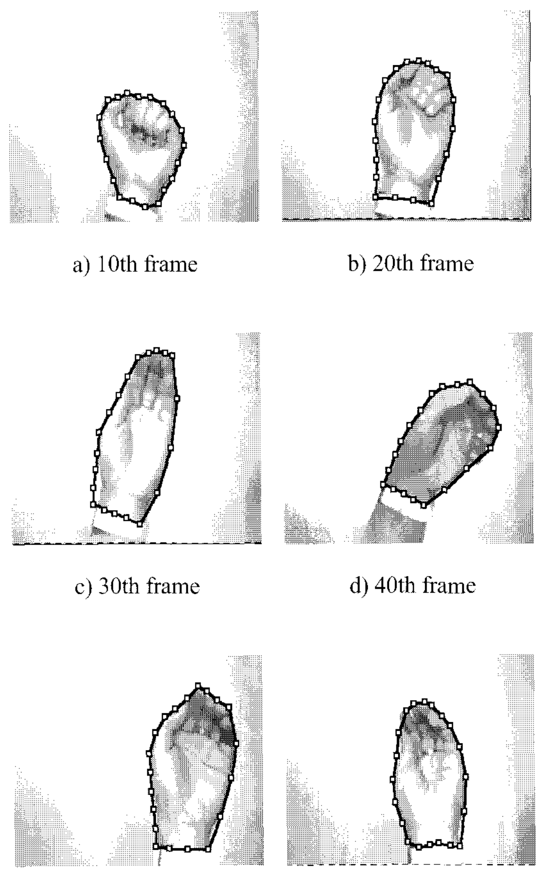
Fig. 9 Edge detection for a spanner



a) Initial contour b) Result image

Fig. 10 Edge detection for scissors

Fig. 11 shows experimental results of tracking a human hand. As shown in results, the active contour settled around the edge of the changing hand. Finally, the position of an object, which was placed on a surface moving forward and backward repeatedly was measured. Fig. 12 shows the experimental layout. 0.15Hz sinusoidal control input was applied to the DC motor because the image board acquired about 7~10 frames per second. Figs. 13 and 14 show experimental results of the edge detection and the measured position of the moving object, respectively. In Fig. 14, 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. At this time, the CCD camera and the moving target were located orthogonally, and the position was measured from relative distance in the image plane. Result shows that the tracking error was within 1.5% for the reference signal although there were large errors during the first period. Through the several experiments, it was found that the performance of tracking depended on the quantity of the nodes of the active contour and the sampling resolution of the image grab board.



a) 10th frame b) 20th frame

c) 30th frame d) 40th frame

e) 50th frame f) 60th frame

Fig. 11 Tracking results for a hand

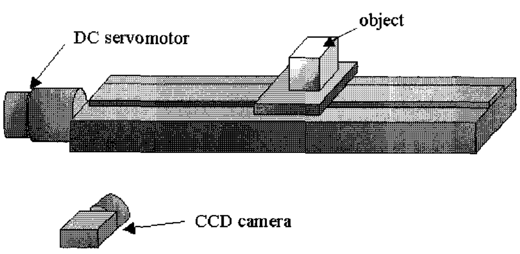
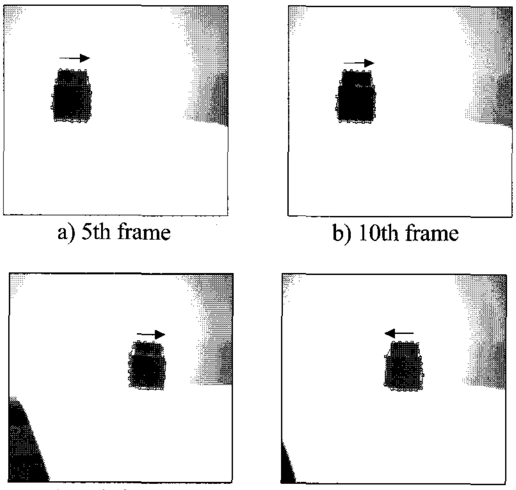


Fig. 12 Layout for the experiment



a) 5th frame b) 10th frame

c) 15th frame d) 20th frame

Fig. 13 Tracking of an object moving forward and backward repeatedly

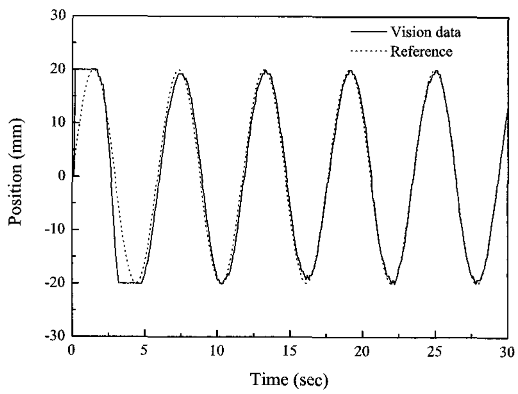


Fig. 14 The position of an object

5. Conclusions

In this paper, the active contour model for computer vision and image analysis were discussed. In order to use the active contour model, a modified energy function was suggested. The proposed energy function was applied for the tracking of a moving object. Moreover, the position of a moving object was measured. Experimental results showed that the proposed internal energy function is suitable for the tracking an edge of the object. Even though there was a large error in the first period, edge tracking was possible because of the low performance of the image board. However, the proposed algorithm for tacking of an edge of the deformable object using an active contour model was verified.

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