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A CORNER TRACKER SNAKE APPROACH TO SEGMENT IRREGULAR OBJECT SHAPE IN VIDEO IMAGE

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ABSTRACT

In this paper we propose a modified version of the classical explicit snake (active contour) approach for the segmentation of irregular object shape in video images. In the classical approach the external evolution force is computed using the gradient of the image or the region information. In our original proposed method the external force is computed using the region information with two windows around the contour point. This new approach improves the speed of convergence and also the quality of segmentation especially for irregular objects shape(objects with sharp corners, deep concave/convex shape). As the contour points are attracted to the discontinuity of form, the modified snake is called ”corner tracker snake”.

***Index Terms*—** Image segmentation, object detection.

1. INTRODUCTION

One principal objective in image processing is the segmentation of the image to recover the shape of objects. Since the work of Kass and al. [1] extensive research on snakes (active contours) was developed with this objective. The first approaches [1][2] minimized an energy function to move the active contour towards edges. Later, another strategy was developed, using region information [3] to overcome some problems inherent of the edge approach. In this paper we are interested in developing a region based snake method in the MDL (Minimum Description Length) framework with the constraint of computation time. There is actually a great interest in level set methods, but the drawback of these approaches is the processing time even with the fast marching method [4]. For this reason we use explicit snake (polygonal). The problem encountered in the classical snake is the smoothness of the contour due to the internal force and the difficulty in this case to adapt the snake to high curvature contour. Increasing the number of contour point reduces the effect, but it still present and increases the computation time. The proposed method modifies the expression of the external force using two windows around the contour point to estimate two forces $(\vec{F}_{left}, \vec{F}_{right})$. Also, the number of contour points is adapted using MDL approach. The classical approaches are presented in section 2, our method is developed in section 3. Experimental results are provided in section 4 on synthetic images and in section 5 on real images.

2. CLASSICAL APPROACHES

A parametric snake is a curve $\Gamma(s) = [x(s), y(s)], s \in [0, 1]$, which minimizes an energy functional by moving throw the spatial domain of an image:

$$E[\Gamma(s)] = E_{int}[\Gamma(s)] + E_{ext}[\Gamma(s)] \tag{1}$$

The energy consists of two energies internal and external. The internal force preserves the smoothness and continuity. The external energy is derived from the information in the image I. A typical energy for a snake using gradient of image is, [2]:

$$E[\Gamma(s)] = \oint_{\Gamma(s)} \left\{ \frac{1}{2}(\alpha \left|\Gamma_s\right|^2) + \beta \left|\Gamma_{ss}\right|^2) - \lambda \left|\vec{\nabla} I \cdot \vec{\nabla} I\right| \right\} ds \tag{2}$$

where $\Gamma_s = \big(\dot{x}(s), \dot{y}(s)\big)$, $\Gamma_{ss} = \big(\ddot{x}(s), \ddot{y}(s)\big)$ and α, β, λ are positive coefficients. For a snake using the region information in the image based on MDL (Minimum description length) we have [3]:

$$\begin{aligned} E[\Gamma, \{\alpha_i\}] &= \sum_{i=1}^{M} \left\{ \frac{\mu}{2} \int_{\delta R_i} ds \right. \\ &- \left. \log P\Big(\big\{I_{(x,y)} : (x, y) \in R_i\big\} \left|\alpha_i\right.\Big) + \lambda \right\} \end{aligned} \tag{3}$$

where R_i is the segmented region i, μ is the code length for unit arc length, M is the number of regions and α_i the parameters of the distribution describing the region i. λ is the code length needed to describe the distribution and code system for region R_i. The external force is processed using a window $W_{(x,y)}$ of m pixels around the control point. Then the equation is now:

$$E[\Gamma, \{\alpha_i\}] = \sum_{i=1}^{M} \left\{ \frac{\mu}{2} \int_{\delta R_i} ds - \int\int_{R_i} \frac{1}{m} \int \int_{W_{(x,y)}} \log P\Big(I_{(u,v)}|\alpha_i\Big) dudvdxdy + \lambda \right\} \quad (4)$$

If we assume that each pixel (x, y) has a multiplicative mixture distribution we obtain:

$$E[\Gamma, \{\alpha_i\}] = \mu \oint_{\Gamma} ds - \int\int_{R} \sum_{i=1}^{M} \pi_{i(x,y)} \log P\Big(I_{(x,y)}|\alpha_i\Big) dxdy + \lambda M \quad (5)$$

where

$$\Gamma = \cup_{i=1}^{M} \partial R_i, \pi_{i(x,y)} = \frac{\|R_i \cap W_{(x,y)}\|}{m}, \sum_{i=1}^{M} \pi_{i(x,y)} = 1$$

The motion equation for point $\vec{v} = (x, y)$ is:

$$\frac{d\vec{v}}{dt} = -\frac{\partial E[\Gamma, \{\alpha_i\}]}{\partial \vec{v}} \quad (6)$$

Using equation (3):

$$\frac{d\vec{v}}{dt} = \sum_{k \in Q_{(\vec{v})}} \left\{ -\frac{\mu}{2} \kappa_{k(\vec{v})} \vec{n}_{k(\vec{v})} + \log P(I_{(\vec{v})}|\alpha_k) \vec{n}_{k(\vec{v})} \right\} \quad (7)$$

where $\kappa_{k(\vec{v})}$ is the curvature, $\vec{n}_{k(\vec{v})}$ is the unit normal to Γ_k at point $\vec{v}$. In the following section we present our approach based on this method.

3. CORNER TRACKER SNAKE

The proposed external force attracts the contour points $\vec{v}$ to the image contour with a high curvature. Actually, using (4) the contour points are attracted to region which maximise the contrast between two regions Ω_{in}, Ω_{out} (if we use only one active contour) but not especially to region of high curvature. This is due to the internal force and also the method using windows $W_{(x,y)}$ around contour points $\vec{v}$ to calculate the external force. We modified the expression of the force to improve the evolution of the snakes:

$$\frac{d\vec{v}}{dt} = \sum_{k \in Q_{(\vec{v})}} \Big\{ \log P(I_{(u_{left}, v_{left})}|\alpha_k) \vec{n}_{k(\vec{v})}^{left} + \log P(I_{u_{right}, v_{right})}|\alpha_k) \vec{n}_{k(\vec{v})}^{right} \Big\} \quad (8)$$

where $\vec{n}_{k(\vec{v})}^{left}$ is the normal unit vector of the left segment of the contour point $\vec{v}$ and $\vec{n}_{k(\vec{v})}^{right}$ is the normal unit vector of the right segment of the contour point $\vec{v}$. In fact the new force is composed of two forces:
$\vec{F_{new}} = F^{left} \vec{n}^{left} + F^{right} \vec{n}^{right}$. Each force is estimated using a window of size m, $W_{(x,y)}^{left}$ and $W_{(x,y)}^{right}$, see figure 1. As the contour point is attracted to the area with great contrast and strong curvature we have removed the internal force based on the curvature which is opposed to our objective. The new energy criterion is:

$$E[\Gamma, \{\alpha_i\}] = \sum_{i=1}^{M} \Big\{ - \int\int_{R_i} \frac{1}{m} \int \int_{W_{(x,y)}^{left}} \log P(I_{(u,v)})|\alpha_i) dudvdxdy - \int\int_{R_i} \frac{1}{m} \int \int_{W_{(x,y)}^{right}} \log P(I_{(u,v)})|\alpha_i) dudvdxdy \Big\} \quad (9)$$

In the MDL Framework [5] the criterion is composed of 2 terms. The first one is the description length, and the second the information required to represent the model parameters:

$$E = \mathcal{L}(I_{(x,y)}|\phi) + \mathcal{L}(\phi) \quad (10)$$

with $\phi = \{\phi_1, ..., \phi_k\}$ the vector of parameters with k components.
In our approach the parameters are: $\phi = \{\gamma, \vec{v}\}$, where γ is the vector of parameters describing the distribution of gray level intensity in the region. The code length to describe the distribution is λ used in the previous criterion, see Eq.(4). The code length describing the contour is related to the number of contour points n_i for each contour. For one point the description length in an image of dimension $M * M$ is [6]:

$$\mathcal{L}_{point} = \log_2 \frac{M}{\epsilon} \quad (11)$$

where ϵ represents the resolution.
Finally, the new energy criterion is:

$$E[\Gamma, \{\alpha_i\}] = \sum_{i=1}^{M} \Big\{ - \int\int_{R_i} \frac{1}{m} \int \int_{W_{(x,y)}^{left}} \log P(I_{(u,v)})|\alpha_i) dudvdxdy - \int\int_{R_i} \frac{1}{m} \int \int_{W_{(x,y)}^{right}} \log P(I_{(u,v)})|\alpha_i) dudvdxdy + \lambda + n_i * \mathcal{L}_{point} \Big\} \quad (12)$$

The number of contour points can be adapted during the convergence of the algorithm. Generally, the number of points is proportional to the length of the snake ($ds = cst$)[2].

3.1. Contour points adaptation

We propose to add contour points if:

$$ds > \epsilon_s \; and \; E_{new} < E_{old}$$

Using the MDL approach, we add a contour point only if the distance between 2 contour points is superior to a constant ϵ_s

and only if the energy with the added contour point is inferior to the energy without the added point. We propose to remove a point if:

$$\arctan\left(\vec{n}^{left}, \vec{n}^{right}\right) < \epsilon_\theta \; and \; E_{new} < E_{old}$$

We remove a contour point only if the angle formed by the vectors $\vec{n}^{left}$ and $\vec{n}^{right}$ is inferior to a constant ϵ_θ, (this is the case when three contour points are aligned) and if the energy decreases.
In the following section we present some results using classical method and our *corner tracker snake* on synthetic images to illustrate the performances.

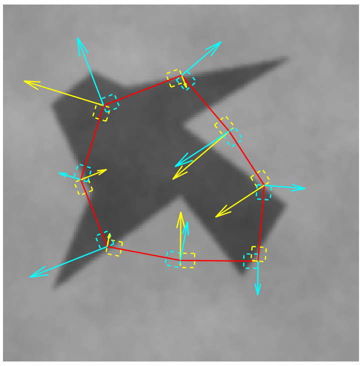


Fig. 1. The snake with the left (yellow) and right (cyan) windows and the estimated forces.

4. RESULTS ON SYNTHETIC IMAGES

In this section we present in first some criterion of performance and in second results on synthetic images. We cannot compare the performances of methods in term only of energy evolution due to the differences of energy expression. Then we propose the following criteria if we have only one active contour separating two regions:

$$C_{good} = \frac{card\{\Omega_{in} \cap \Omega_o\}}{card\{\Omega_o\}}, C_{false} = \frac{card\{\Omega_{in} \cap \Omega_b\}}{card\{\Omega_b\}}$$

where Ω_{in} is the internal region of the snake, Ω_o the region of the object to detect, Ω_b the region of the background. The first result is presented on synthetic image without noise with high contrast. The number of contour point is increasing proportionally to the length of the snake in this demonstration. We obtain better result with our method, see figure 2, than with classical method with a number of contour point proportional to the length (ds=60). To understand the difference of results between the two methods we have zoomed on the figure 2 when the algorithms have converged, see figure 3. The problem of convergence encountered for the classical region snake is corrected with the *corner tracker snake*. In this approach the number of contour points is not optimal to describe the contour of the structured object, then we propose to use the method presented in 3.1 for the *corner tracker snake*. The second result is presented for an irregular object shape with noise, see figure 4. We compare the *corner tracker snake* approach, the minimal description length *corner tracker snake*, and the classical snake. To obtain the same kind of performance with the classical approach, see table 1, we must have a lot of contour points. Even with this improvement the classical approach gives lower results due to the smoothness of the contour.

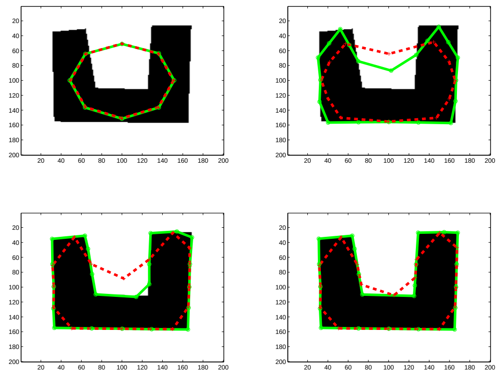
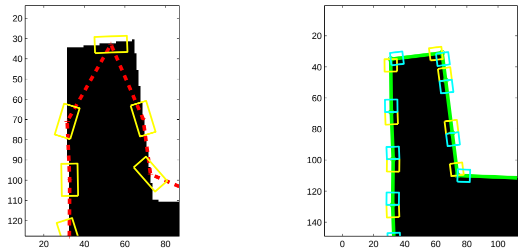


Fig. 2. In green the *corner tracker snake*, in red dashed the classical region snake.

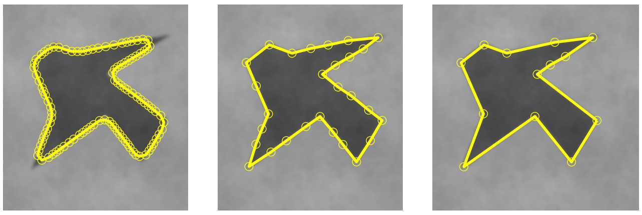


(a) (b)

Fig. 3. (a)the classical region snake in dashed red and the windows around contour points in yellow,(b) the *corner tracker snake* in green and the left windows in yellow and the right windows in cyan.

5. RESULTS ON REAL APPLICATION

The application concerns the European project PEGASE (helicoPter and aEronef naviGation Airborne System Experimen-



(a) (b) (c)

Fig. 4. (a) classical region snake with 100 contour points, (b) the *corner tracker snake* with 28 contour points, (c) the *corner tracker snake* with minimun descrition length with 13 contour points.

snake Method	C_{good}	C_{false}	time	time 90%	iter. 90%
corner tr.	98,59%	0.46%	4,5s	0,89s	8
corner tr. MDL	98,42%	0.43%	7,28s	1,53s	9
classical	96,67%	0.64%	7,89s	2,25s	11

Table 1. Results of classification. We present the processing time for 30 iterations, the processing time (MATLAB) and the number of iterations to obtain 90% of good classification. We have improved the classification and the processing time with the corner tracker snakes.

tation). The objective is to track a detected runway in a sequence of visible or infrared images to control the landing of a wing aircraft. In the proposed approach, the runway is parametrised by two parallel lines used as image features. The *corner tracker snake* appears to be well adapted for this kind of problem, because the projection of the runway in the image is a convex quadrangle. The tracking method must be fast due to the constraint of real time. For this application we propose to use a snake with only four contour points. With a classical region snake this number of contour points will not be enough. The results are presented in the following figures 5,6,7. The snake is initialized roughly, in the center of the object to track, in the first image, in the following images we use the previous position as initial position. The runway is correctly detected and tracked through the sequence in real time.

Fig. 5. Frame 10

Fig. 6. Frame 150

Fig. 7. Frame 270

6. CONCLUSION

In this paper we have presented an original and efficient snake approach to segment images of irregular object shape. We have shown the improvement of performance in terms of computation and segmentation compared to classical method (region based snake).The approach has been also used on real images with satisfactory results. In the future, we will develop a multi-snake approach along with a method to initialize the position of the snake in the image.

7. REFERENCES

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