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Emerald Article: Two-step active contour method based on gradient flow

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Two-step active contour method based on gradient flow

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Abstract

Purpose – Active contour can describe target's silhouette accurately and has been widely used in image segmentation and target tracking. Its main drawback is huge computation that is still not well resolved. The purpose of this paper is to optimize the evolving path of active contour, to reduce the computation cost and to make the evolution effectively.

Design/methodology/approach – The contour-evolution process is separated into two steps: global translation and local deformation. The contour global translation and local deformation are realized by average and normal gradient flow of the evolving contour curve, respectively.

Findings – When a contour is far away from the object to be segmented or tracked, the effective way of contour evolution is that it moves to the object without deformation first and then it deforms into the shape of the object when it moves on the object.

Originality/value – The method presented in this paper can optimize the curve evolving path effectively without complicated calculation, such as rebuilding a new inner product, and its computation cost is largely reduced.

Keywords Robotics, Tracking, Deformation, Flow

Paper type Research paper

1. Introduction

Active contour model, also known as snake model, was pioneered in 1987 by Kass *et al.* (1987) for image segmentation via driving an initial contour toward a desired object edge with a PDE deduced by minimizing energy functional. Active contour can describe targets accurately, so it is widely used in image segmentation and target tracking. In 1993, geodesic active contour, formulated as a weighting Euclidean arc length using an edge-stopped potential functional, was proposed by Caselles *et al.* (1993) in a level set framework (Osher and Sethian, 1988). It is independent of curve parameterization and can easily handle curve topological changes. Those models mentioned above are edge-based (Caselles *et al.*, 1993; Osher and Sethian, 1988; Kichenassamy *et al.*, 1995; Xu and Prince, 1998). In most cases, they are less robust for image segmentation than region-based active contour models (Zhu *et al.*, 1995; Chan and Vese, 2001; Yezzi *et al.*, 2002; Kim *et al.*, 2005) because the latter models utilize certain image global region statistical information which partitions a given image into statistically distinct regions. In order to obtain desirable segmentation results, one important strategy for active contours research is combining certain prior knowledge with image information (gradient and region information, etc.) to deal with images with insufficient information. The shape and topology of objects to be segmented are important prior information. Some paradigms using prior shape and topology information can be found in Leventon *et al.* (2000), Chen *et al.* (2002), Cremers (2006), Han *et al.* (2003) and Sundaramoorthi and Yezzi (2005). For more recent developments about active contours, we refer the readers to Cremers *et al.* (2007) and Chan *et al.* (2006).

Before the appearances of Charpiat *et al.* (2007 and Sundaramoorthi *et al.* (2007), many literatures on active, contours focused on energy functional building, while they ignored the effect of gradient flows in curve evolving completely. Sometimes, the arbitrary evolution of active contour results in many undesirable segmentation and tracking results. As shown in Figure 1, the velocity field of the points along the contour is irregular that often leads to the unnecessary shape change during the evolution of the contour which is shown in Figure 2. In order to entitle contour evolution to certain desirable

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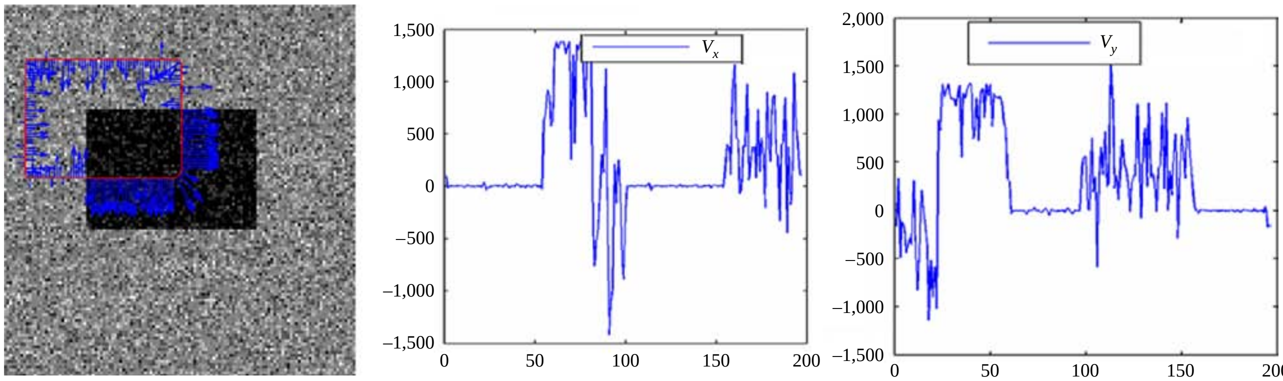
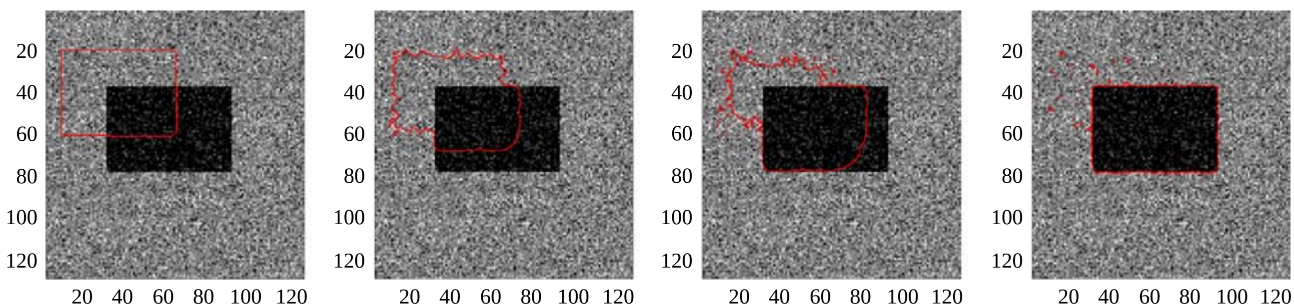
Figure 1 Velocity field of a curve without control



(a) (b) (c)

Notes: (a) Velocity field of a curve; (b) V_x of the curve; (c) V_y of the curve

Figure 2 The evolution of the curve with the uncontrolled velocity



(a) (b) (c) (d)

Notes: (a) The initial contour; (b) 200 iterations; (c) 400 iterations; (d) 1,200 iterations

features to reduce this useless shape changing and to escape irrelevant local minimums, prior information on the deformation field of evolving contours can also be used. Charpiat showed that the gradient of a given energy can also be considered as the result of a minimization problem from a new point and extended the definition of gradient toward more general priors (Charpiat *et al.*, 2007). Sundaramoorthi *et al.* (2007, 2009) proposed the H^1 active contour whose gradient flow is defined using the H^1-type inner product and discussed the new possibilities of this active contour.

In this paper, a new active contour based on the analysis of average gradient flow called as two-step active contour is proposed. This active contour possesses the properties of separated global transformation and local deformation, but needs not change the inner product and can be implemented by level set method easily and fast. It possesses the properties of prior global transformation and fast local deformation.

The outline of the paper is as follows. In the next section, we introduce the definition of H^1 active contour. In Section 3, our new active contour method is presented. Some experiments and comparison are presented in Section 4, which is followed by some conclusions in Section 5.

2. H^1 active contour

Let M denote the set of smooth embedded curves in R^n, which is a differentiable manifold. For $C \in M$, the tangent space of M at C is denoted by $T_C M$, which can be seen as the deformation space. Given an energy function $E(C)$, for all admissible deformation fields v defined on C, its Gateaux derivative $\delta E\ (C,\ v)$ can be expressed as:

$$\delta E(C, v) \overset{\text{def}}{=} \lim_{\varepsilon \to 0} \frac{E(C + \varepsilon v) - E(C)}{\varepsilon} = \mathrm{d}E(C) \cdot v \qquad (1)$$

In order to get the gradient flow of $E(C)$, we must model the deformation space $T_C M$ as an inner product space denoted by $(F, \langle , \rangle_F)$. The gradient flow $\nabla_F E(C) \in T_C M$, which is relative to the defined inner product exist when it satisfies the following conditions:

$$\forall \eta \in T_C M \quad \delta E(C, \eta) = \langle \nabla_F E, \eta \rangle_F \qquad (2)$$

The inner products for H^0 and H^1 active contours are defined as following:

$$\begin{aligned} \langle h, k \rangle_{H^0} &:= \tfrac{1}{L0} \int h(s) \cdot k(s)\, \mathrm{d}s \\ \langle h, k \rangle_{H^1} &:= \langle h, k \rangle_{H^0} + \lambda L^2 \langle h', k' \rangle_{H^0} \end{aligned} \qquad (3)$$

where $\lambda \geq 0$ is a weighting coefficient, L is the length of C, $h(s)$ and $k(s \in T_C M)$ parameterized by the arclength of curve and the derivatives on $h(s)$ and $k(s)$ are with respect to arclength. At last, the relation between gradient flows for H^0 and H^1 active contours can be established by solving an ODE derived via relations between H^0 and H^1 inner products defined above:

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$$\nabla_{H^1} E = \nabla_{H^0} E \cdot K_\lambda \tag{4}$$

$$K_\lambda(s) = \frac{\cosh\left((s - L/2)/\sqrt{\lambda}L\right)}{2L\sqrt{\lambda}\sinh\left(1/2\sqrt{\lambda}\right)} \tag{5}$$

H^1 active contour has many advantages over traditional H^0 active contour, such as favorable global translations, better regularity properties which make the H^1 active contour more suitable for object tracking. However, H^1 active contour is a convolution of H^0 active contour and a kernel functional, and hard to be realized by level set methods without polygon extraction.

3. Two-step active contour

3.1 The average gradient flow and the motion of the active contour

The H^0 (L^2-type) inner product is the most common and useful inner product by now. In H^0 inner product, we get the following relation:

$$dE(C) \cdot v = \frac{1}{L}\int_C \nabla E_{H^0} \cdot v ds = \langle \nabla E_{H^0}, v \rangle_{H^0} \Rightarrow \frac{\partial C}{\partial t} = -\nabla E_{H^0} \tag{6}$$

where L is the length of C, and the gradient flow ∇E_{H^0} can be computed via variational active contour method. The opposite of the H^0 gradient flow is denoted by:

$$v0 = -\nabla E_{H^0} \tag{7}$$

Let:

$$\overline{v0} = \frac{1}{L}\int_C v0 \mathrm{d}s \tag{8}$$

$\overline{v0}$ is called average gradient flow. It can reflect the motion state of the active contour.

Figures 3(d) and 4(d) show the $\overline{v0}$'s change with the evolution of the curve. The red one is the V_x: the x component of $\overline{v0}$, the green one is the V_y: the y component of $\overline{v0}$ and the blue one is V: the magnitude of $\overline{v0}$, where $V = \sqrt{Vx^2 + Vy^2}$. The abscissa is the iteration number and the ordinate is value of $\overline{v0}$' components.

Analyzing those figures, we learn that at the beginning of evolution, when the curve is far away from the object, the average evolution speed is high; as the curve moving nearby the object, the average evolution speed will be slowed down. In other words, when the average gradient flow's magnitude is over a certain threshold, the active contour is in global translation; otherwise, the active contour is in local deformation.

3.2 Global translation active contour

To make the evolution in global translation more effective, we propose a global translation active contour model, in which a global deformation Vg is the global translation velocity of the curve. As shown in Figure 5, all parts in the curve move in the same direction and speed. In the global translation active contour, the curve evolves as equation (9):

$$\frac{\partial C}{\partial t} = Vg \tag{9}$$

Supposing that this method does not change the Gateaux derivative of C, we can get:

$$dE(C) \cdot v = dE(C) \cdot Vg \tag{10}$$

that means:

$$\begin{aligned} \langle \nabla E_{H^0}, v \rangle_{H^0} &= \frac{1}{L}\int_C \nabla E_{H^0} \cdot v \mathrm{d}s = \frac{1}{L}\int_C \nabla E_{H^0} \cdot Vg \mathrm{d}s \\ &= \frac{Vg}{L}\int_C \nabla E_{H^0} \mathrm{d}s = \langle \nabla E_{H^0}, Vg \rangle_{H^0} \end{aligned} \tag{11}$$

Vg satisfies equation (12):

$$\int_C v0 \cdot v0 \mathrm{d}s = Vg \cdot \int_C v0 \mathrm{d}s \tag{12}$$

which is deduced from equations (7), (8) and (11). Equation (12) implies that Vg with the smallest magnitude has the same direction with average gradient flow $\overline{v0}$.

3.3 The two-step active contour based on average gradient flow

One of the important advantages of active contour is the excellent ability to describe the local deformation of objects exactly. It is necessary to replace the translation active contour by the active contour, which allows the shape deformation of curves (traditional active contours), when the active contour closes to the object. According to Figure 3 and 4 and the analysis in Section 3.1, the average gradient flow $\overline{v0}$ will be slowed down when curve evolves nearby the object. Therefore, the magnitude of $\overline{v0}$ can be used to decide the motion of contour. This evolving process can be represented by equation (13) and Figure 6:

Figure 3 The evolution and the $\overline{v0}$ distribution of a noise circle

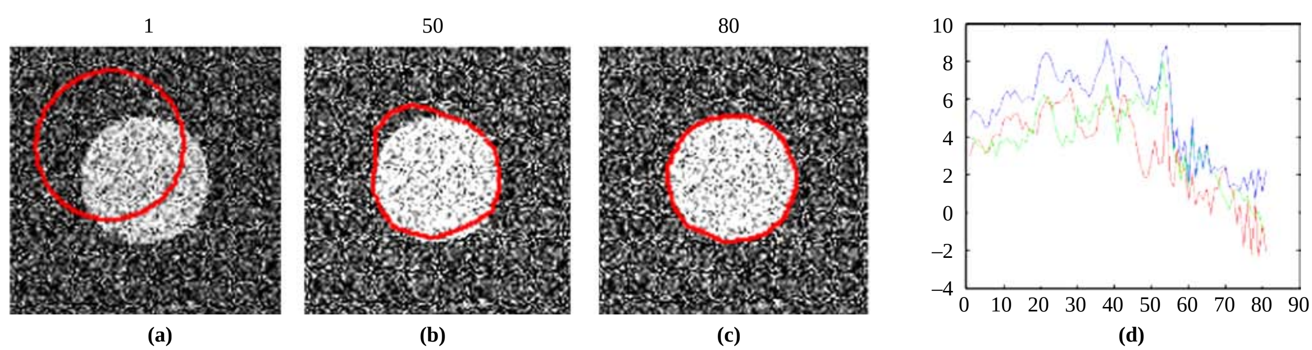

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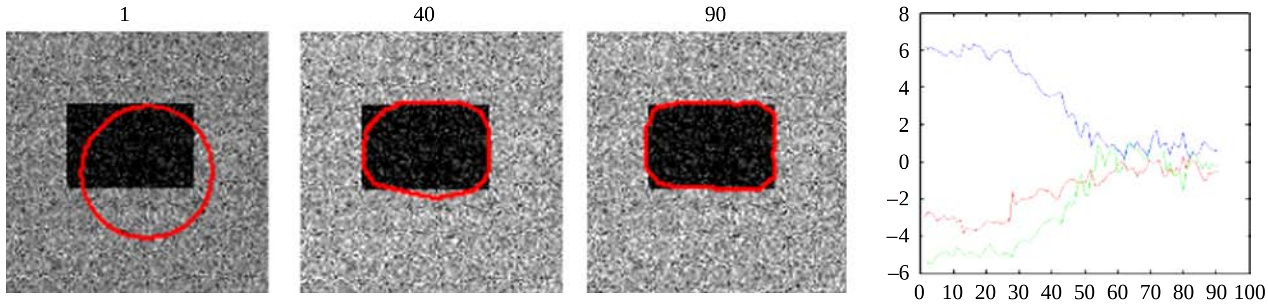
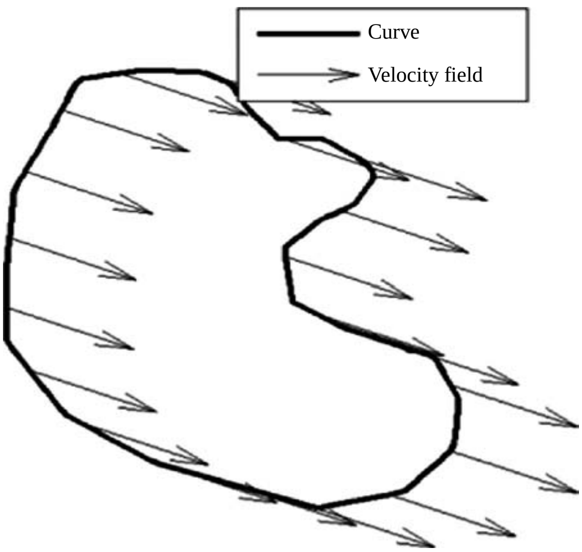
Figure 4 The evolution and the $\overline{v0}$ distribution of a noise rectangle



(a) **(b)** **(c)** **(d)**

Figure 5 Equal velocities along the evolving curve



$$\frac{\partial C}{\partial t} = \begin{cases} Vg & \text{when } \|\overline{v0}\| > \text{threshold} \\ v0 & \text{otherwise} \end{cases} \tag{13}$$

Figure 6(a) is the target and the initialized contour. In Figure 6(b), the contour translates to the location of the target. Then the contour evolves to the right shape as shown in Figure 6(c).

The selection of the threshold, which decides the switch point between global translation and local deformation, is a key problem of our method. Different energy function, different parameters, and different kind of images make the value of average gradient flow different, so the threshold in each case is decided by the average value of first fifth iterations. Usually, we set the threshold as the equation (14):

$$\text{threshold} = \frac{\text{AverageVelocity}}{3} \tag{14}$$

where the AverageVelocity is the mean value of first fifth iterations.

In our method, we do not define a new inner product to control the evolution of curves. The gradient flow deduced from H^0 inner product is used in the separated processes: global translation with average gradient flow and local deformation with normal gradient flow.

4. Experiments

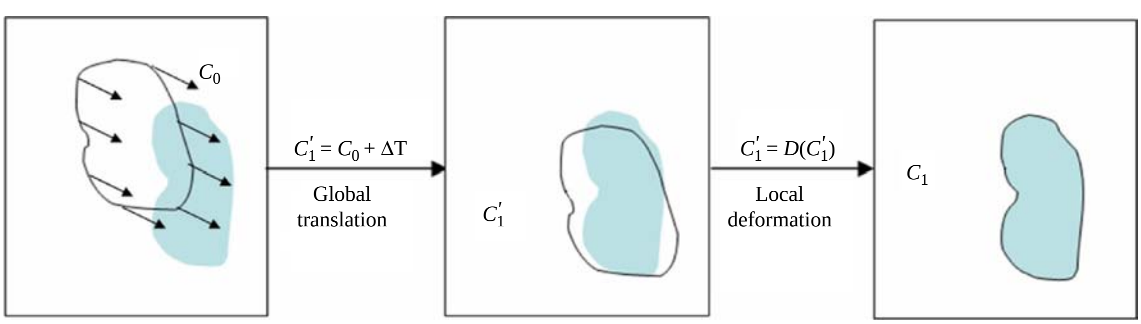
4.1 Comparison among H^0, H^1 and proposed method

We compare our method with the traditional H^0 active contour and H^1 active contour by the parameterized curve (Kass *et al.*, 1987) with the same initial contour and energy parameters (Figure 7).

Table I gives the comparisons of Figure 6 among H^0 active contour, H^1 active contour and our method. In H^1active contour and H^0, active contour we define the iterations before the contour around the object as the translation. From Table I, we can deduce that:

- *Global translation.* H^0 active contour use most translation iterations, because in H^0 active contour the global translation and the deformation are happened in the same time. The translation of H^1active contour is close to the iterations of our two-step active contour, but the iteration time of H^1 active contour is longer.

Figure 6 The evolving course of proposed method



(a) **(b)** **(c)**

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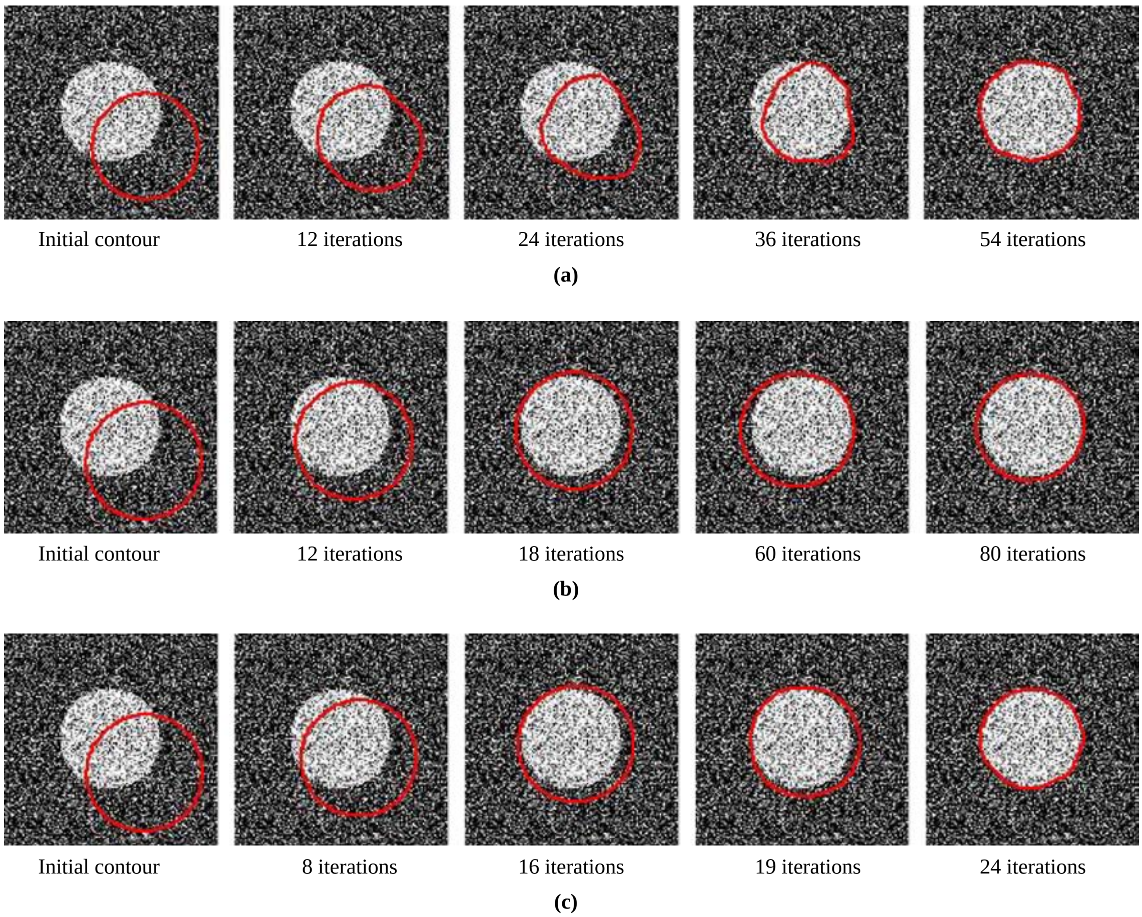
Figure 7 The comparison of evolve results of H^0,H^1 and two-step active contour for a object in noise



Notes: (a) H^0 active contour; (b) H^1 active contour; (c) The proposed method-two-step active contour

Table I Comparison in Figure 7

Methods	Translation iterations	Translation times (s)	Deformation iterations	Deformation times (s)	Total times (s)
H^0	38	0.96	16	0.47	1.43
H^1	18	0.77	68	3.05	3.82
Two-step	16	0.42	8	0.22	0.64

- *Local deformation.* The H^1active contour characteristic of keeping curve smooth makes it take much longer time in deformation than the H^0 and two-step active contours. In the local deformation process, two-step active contour method is the H^0 active contour which can change shape to fit the object boundary easily.
- The total iterations of two-step active contour is less than the H^0 and H^1 active contours, and the consuming time of two-step active contour is the least one among these method.

4.2 Segmenting results

Object segmentation is implemented by the proposed method and the traditional H^0 active contour (with gradient flow without separation of global translation and deformation). The curves are represented by the level set method (Osher and Sethian, 1988). The energy models we used for segmenting is the C-V active contour model (a region-based model) which is proposed in reference Chan and Vese (2001).

The segmentation results on synthetic image are show in Figure 8. Figure 8(a)-(e) shows the $\overline{v0}$ distribution with the curve evolving and the evolving results by our method. Meanwhile, Figure 8(f)-(j) shows the $\overline{v0}$ distribution and evolving results by H^0 active contour with the same initial curve, energy functional and parameters. The convergence of $\overline{v0}$ by our method is faster compared to that of the traditional method, as shown in the following distribution maps, i.e. the curves in our method can move to the object faster and get convergence in less iteration. It is validated by the evolving results of active contour in Figure 8.

The segmentation results for real images are shown in Figure 9. The $\overline{v0}$ distribution with the curve evolving and the evolving results by our method are shown in Figure 9 (a)-(e). Figure 9 (f)-(j) shows the $\overline{v0}$ distribution and evolving results by H^0 gradient flow without separation of translation and deformation. The initial curve, energy functional and parameters are same in these methods. The results show

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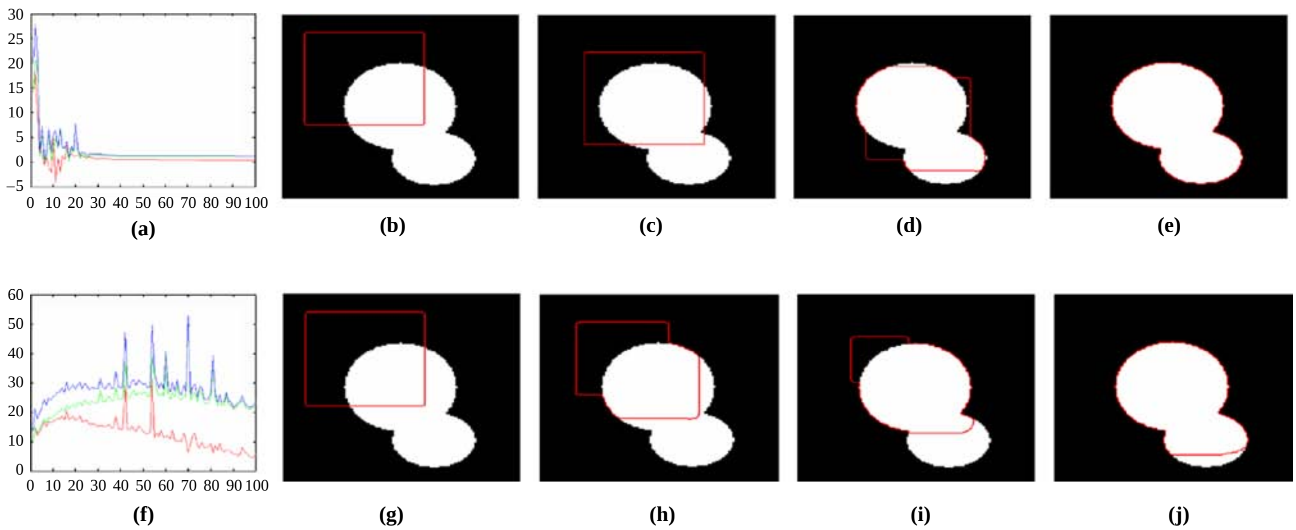
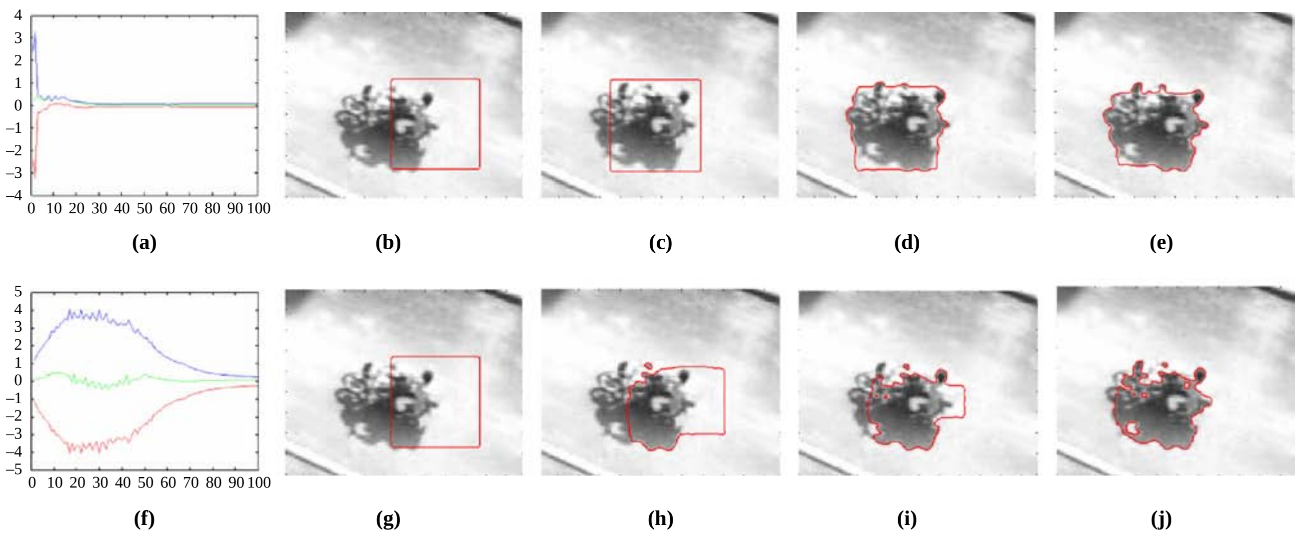
Figure 8 The evolve results by proposed method (a)-(e) and traditional H^0 method for two circles



Notes: (a) $\overline{v0}$ distribution; (b) initial contour; (c) 20 iterations; (d) 60 iterations; (e) 800 iterations; (f) $\overline{v0}$ distribution; (g) initial contour; (h) 60 iterations; (i) 300 iterations; (j) 1,000 iterations

Figure 9 The evolve results by proposed method (a)-(e) and traditional H^0 method for a motor with persons



Notes: (a) $\overline{v0}$ distribution; (b) initial contour; (c) 20 iterations; (d) 60 iterations; (e) 100 iterations; (f) $\overline{v0}$ distribution; (g) initial contour; (h) 100 iterations; (i) 300 iterations; (j) 500 iterations

that our proposed method reduces the iteration times and brings the better segmentation results.

Figure 10 shows an interesting experiment. In this synthetic image, there is a small object beside a big object. If we use our method to segment Figure 10(a)-(e), the initial active contour will move across the small object and stop on the big one, and only the big object is segmented. For object tracking, it can be used to avoid the disturbance of some small objects. In the segmentation results Figure 10(f)-(j) with a traditional method, both the objects are segmented, the iteration times is much more.

4.3 The tracking results

The proposed active contour method is also implemented in target tracking. We initialize the active contour as a rectangle according to the location and the size of the object on the start-tracking-frame. The evolution in every frame is shown in Figure 6. After the curve evolving in the current frame, the evolution result will be saved as the initial contour for the next frame. In object tracking, usually, the global translation is the obvious change of object between two conjoint frames and the shape of object is slowly changed in its motion. So, the global translation preferred character of our method is very congruous to the feature of object motion, and the shape of initialized contour in each frame is close to the object's shape. From the comparison result in Table I, it shows that our method is the most effective one in single frame among three methods, and it is also effective in object tracking among sequence frames. Some results are shown below.

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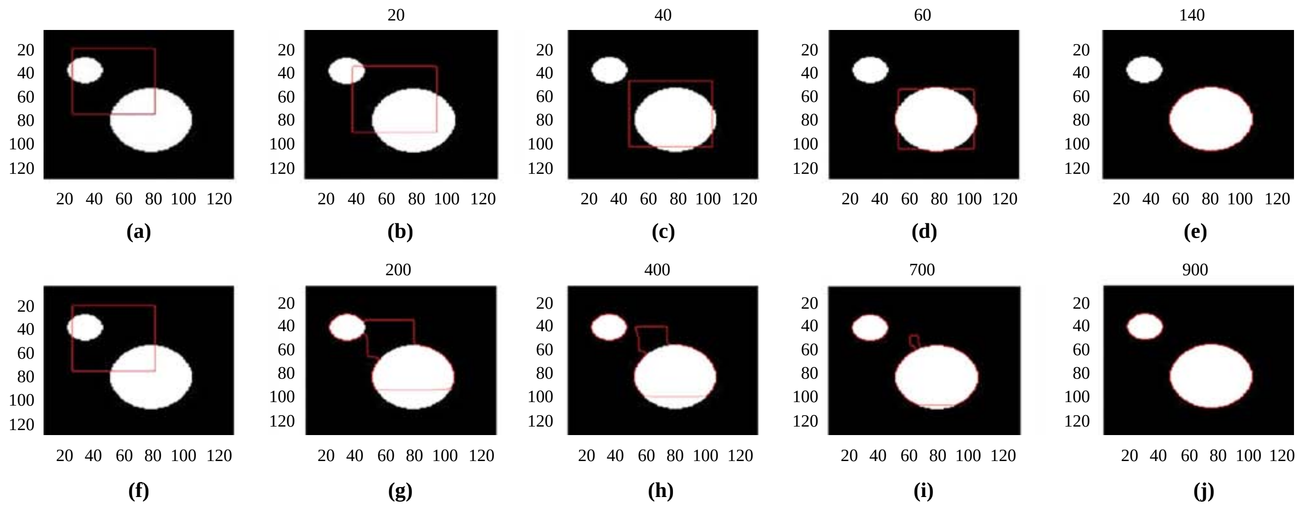
Figure 10 The evolve results by proposed method (a)-(e) and traditional H^0 method for a object with disturbance



Notes: (a) Initial contour; (b) 20 iterations; (c) 40 iterations; (d) 60 iterations; (e) 140 iterations; (f) initial contour; (g) 200 iterations; (h) 400 iterations; (i) 700 iterations; (j) 900 iterations

The tracking results are shown in Figure11 and 12. The car video sequence has 220 frames with the pixel resolution 320×240. Because of the complex background, we use the Geodesic active contour models (an edge based model) (Caselles *et al.*, 1993) to track the car in these frames. We implement our method with Matlab platform, and it takes 0.094 s to handle each frame in average, the average iteration number is 19.64. And the average iteration number for traditional H^0 method is 40. For the frames of object with occlusion, this sequence has 100 frames with the pixel resolution 640×480. The C-V active contour is used to get the silhouette of the object. It takes 0.266 s to handle each frame in average, the average iteration number is 25.22. The average iteration number for traditional H^0 method is 60 which is higher than our method. When an object is partly occluded, its real boundary can be retained and detected with our method because the global translation leave a good initial contour for the local deformation. From the results, we can see that even in dynamic and complex background, our method can track object accurately and effectively.

5. Conclusions

A two-step active contour that divides the evolution of active contour into global translation and local deformation is proposed. The average gradient flow is used to determine the motion of the curve. The global deformation variable Vg is computed and represents the global translation of the curve when the evolving curve is far away from object. After the curve is close to the object, the local deformation replaces the global translation; then silhouette of the object will be segmented. The global translation active contour optimizes the evolving path. The local deformation process keeps the good quality of H^0 active contour. Because of these characters of two-step active contour, this method can reduce the iterative times and get the better evolving results.

Figure 11 The tracking results for a car with rotation

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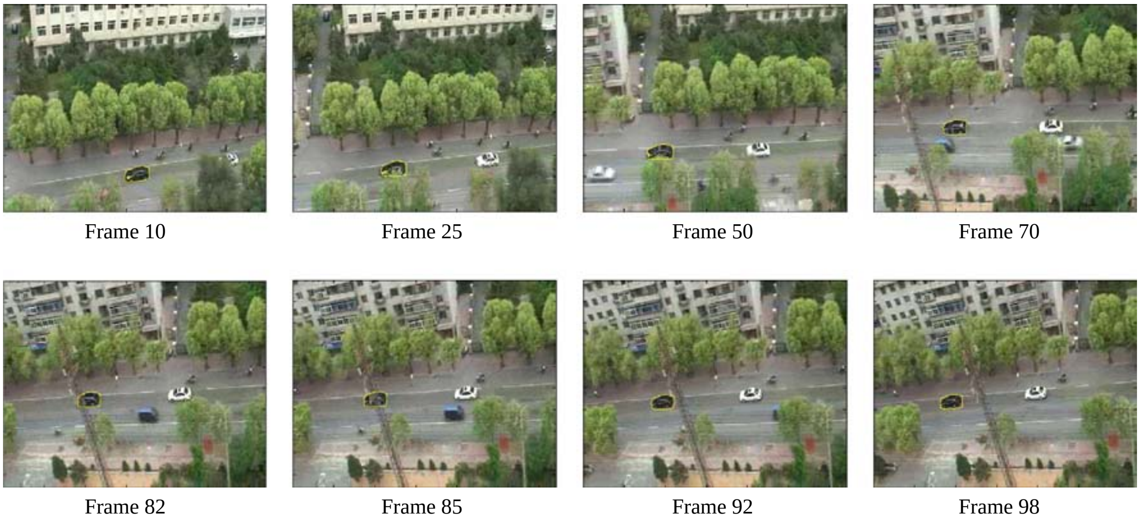
Figure 12 The tracking results for the object with occlusions



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