Snakes reparameterization for noisy images segmentation and targets tracking

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Abstract: Active contours or snakes are very popular tools for image segmentation and video tracking. Unfortunately, the utility of this method is limited in the noisy images, because the noise disturbs the evolution of snake, which leads to detect a wrong object. To overcome this problem, in this paper we propose an efficient method of parameterization; this method gives good results and can be applied in objects tracking.

I. Introduction:

Active contours or snakes are curves or surfaces that move within an image domain to capture desired image features. The first model of parametric active contour was proposed by Kass et al. [1] and named snakes due to the appearance of contour evolution. This first model doesn't have large capture range: we must initialize the snake close to the true boundaries. Thereafter, numerous methods have been developed to improve the capture range problems, including the balloon force [2], distance potential forces [2], multi-resolution methods [4], gradient vector flow (GVF) [5], its generalization: generalized gradient vector flow (GGVF) [6], and vector field convolution (VFC) [7]. The GVF and VFC snakes are popular due to their abilities of attracting the active contour toward object boundary from a sufficiently large distance and the ability of moving the contour into object cavities, and these two properties doesn't exist in other models.

However, the later fields are easily influenced by noise and they have limited success in tackling noise. To address this problem, the authors of [8] demonstrate that a better utilization of structural information is more efficient and can significantly improve noise robustness. There are about two decades [9], it has been proven that multi-resolution active contours reduce noise sensitivity and provide faster convergence. To reduce the effect of high noise levels, the authors of [10] introduce the concept of a multi-scale tensor vector field, which helped to significantly improve the results of segmentation. In [11], we proposed to adapt the parameter controlling the degree of smoothness of the gvf field according to the local variance; the qualitative and quantitative results are satisfactory. In the Sobolev active contours [12], the active contour model is reformulate by redefining the notion of gradient in accordance with Sobolev-type inner products, this method represents a noteworthy advance and gives good results for medium noises.

This paper is a continuation of efforts to overcome the difficulty of traditional parametric snake's model to attain the true target in the noisy images case. Our method is different from the existing methods, it exploits the following idea: we can avoid the effect of noise if we make a perturbation of the points of the active contours during its evolution. We will see that this idea is also particularly useful in tracking applications. The rest of this paper is as follows: Section 2 briefly recalls the traditional snake and GVF, VFC methods. In Section 3, we explain how and why the noise disturbs the evolution of snakes, and then we expose in detail our idea to overcome this problem. In section 4, we show and we commit an example of successful tracking in real world video sequences by our method of parametrization. Section 5 gives the conclusions.

II. Background

1) Parametric active contours

An active contour or snake is represented by a parametric curve $v(s) = [x(s), y(s)]$, $s\epsilon[0,1]$ that deforms and move through the image domain to minimize the energy functional:

$$E = \int_{2}^{1} \frac{1}{2}\left(\alpha|v'(s)|^2 + \beta|v''(s)|^2 + E_{ext}\big(v(s)\big)\right) ds \qquad (1)$$

Where α and β are pre-determined weighting parameters controlling the smoothness and tautness of the contour, respectively. E_{ext} denotes the external energy that is the issue mostly discussed in active snake models. The external energy E_{ext} is defined on the entire image domain so that the desired features, e.i. edges, would have lower values. It is easy to show that the $v(s)$ that minimizes E must satisfy the Euler–Lagrange equation:

$$\alpha v''(s) - \beta v''''(s) - \nabla E_{ext} = 0 \qquad (2)$$

Which can be considered as a force balance equation:

$$F_{int} + F_{ext} = 0 \qquad (3)$$

Where $F_{int} = \alpha\, v''(s) - \beta\, v''''(s)$ is the internal force that controls the smoothness of the snake and $F_{ext} = -\nabla E_{ext}(x, y)$ is the external force that pulls the snake towards the desired image contour. To find a solution of equation (2), the snake is made dynamic by treating v as function of time t as well as-i.e. $v(s,t)$. Namely, we solve:

$$\begin{cases} \frac{\partial}{\partial t} v(s,t) = \alpha\, v''(s,t) - \beta\, v''''(s,t) - \nabla E_{ext} \\ v(s,0) = v_0(s) \end{cases} \qquad (4)$$

A numerical solution of the above equation can be achieved by discretizing the equation and solving the discrete system [1, 3].

2) Gradient vector flow

In traditional active contours model [1], the external force is based only on edge information. Therefore the external force has a large magnitude only in the immediate vicinity of the boundary. Since this external force has small capture range, the initial snake must be carefully chosen to be close to the true boundaries.

Several researchers proposed alternatives solutions to increase the capture range of the external force (see [2,5,6,7]), the most popular and first solution is, the Gradient Vector Flow (GVF) [5] and its generalization, the GGVF [6].GVF is an external force field $(u(x,y), v(x,y))$ constructed by diffusing the edge map gradient vectors (edge force)(f_x, f_y) away from edges to the homogeneous regions, at the same time keeping the constructed field as close as possible to the edge force near the edges. This is achieved by minimizing the following energy functional:

$$E(U,V) = \frac{1}{2}\iint\left(\mu\left(U_x^2 + U_y^2 + V_x^2 + V_y^2\right) + \left(f_x^2 + f_y^2\right)\left[\left(U - f_x\right)^2 + (V - f_y)^2\right]\right)dxdy \quad (5)$$

Where μ is a non-negative parameter expressing the degree of smoothness of the field (U,V). The interpretation of this equation is straightforward; the first integrand keeps the field, (U,V) smooth. The second integrand forces the vector field to resemble the initial edge force near the edges (i.e., where the edge force strength is high). Using the calculus of variation, the GVF can be determined by solving the Euler equations:

$$\mu\nabla^2 V - \left(f_x^2 + f_y^2\right)\left(V - f_y\right) = 0 \quad (6)$$

$$\mu\nabla^2 U - \left(f_x^2 + f_y^2\right)\left(U - f_x\right) = 0 \quad (7)$$

Solving (6) and (7) for ***(U, V)*** results in gradient vector flow (GVF) that acts as an external force field for the active contour. Once the GVF force field ***(U, V)*** is computed via (6) and (7), he is replacing the external force in the snake evolution equations as follow:

$$\frac{\partial X}{\partial t} = \alpha\frac{d^2 X}{ds^2} - \beta\frac{d^4 X}{ds^2} + U(X,Y) \quad (8)$$

$$\frac{\partial Y}{\partial t} = \alpha\frac{d^2 X}{ds^2} - \beta\frac{d^4 X}{ds^2} + V(X,Y) \quad (9)$$

The GVF field provides a large capture range and the ability to capture the boundary concavities [5, 6]. He is widely used in the segmentation process by active contours.

3) Vector field convolution

The vector field convolution (VFC) is an effective external force for active contour model [7]. In VFC, the external field $\boldsymbol{v}$ is generated by convolving the image edge-map f with an isotropic vector field kernel $\boldsymbol{k}$**.** The prefixed vector kernel k is defined as:

$$k(x,y) = m(x,y) \cdot n(x,y) \quad (10)$$

Where $m(x,y)$ is the magnitude of the vector at (x,y), and $n(x,y)$ is the unit vector pointing to the origin (note that the origin of the discrete kernel is located at the center of the matrix k).

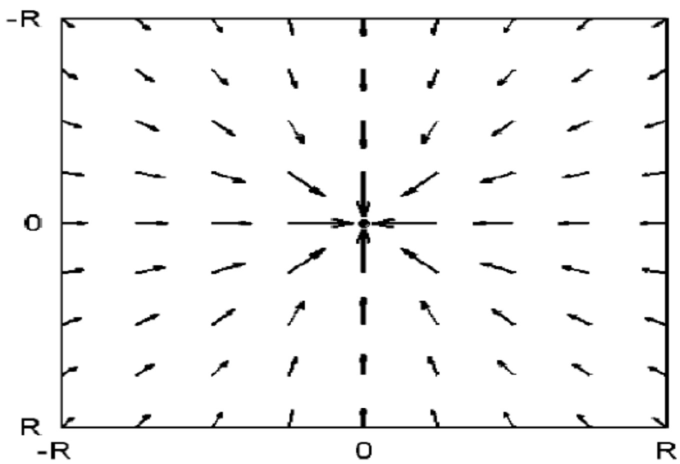


Figure 1: An example of the VFC kernel $\boldsymbol{k}(x,y)$

The direction of vectors of k at each position (x,y) is given as:

$$n(x,y) = [-\frac{x}{r}, -\frac{y}{r}],\ r = \sqrt{x^2 + y^2} \quad (11)$$

Where, x, y are positions with respect to the kernel's center. The magnitude m of kernel's vector element is given by:

$$m(x,y) = (r+\epsilon)^{-\gamma} \text{ or } m(x,y) = \exp\left(-\frac{r^2}{\sigma}\right) \quad (12)$$

If we split k into its x-component $k_x(x,y)$ and its y-component $k_y(x,y)$, the field v (VFC) is given by:

$$v(x,y) = f(x,y) * k(x,y) = [f(x,y) * k_x(x,y), f(x,y) * k_y(x,y)] \quad (13)$$

Once the VFC force field is computed via (13), it replaces the external force in the snake evolution in the same manner as GVF field.

In this method (VFC), the field is calculated using a simple convolution of the edge map with a user-defined vector field kernel. This simplicity combined with its robustness to noise makes the VFC a very promising technique. As compared to gradient vector flow [5], VFC yields improved robustness to noise and initialization. It also allows a more flexible force field definition and a reduced computational cost [7, 14].

III. Active contours reparameterization

1) Problem

Two major challenges are faced in active contours: the poor capture range and the high sensitivity towards noise. Let us see how the noise affects the evolution: the GVF and VFC fields are calculated from the edge map, if the image is noisy, we will have parasitical contours, which leads to a messy field, preventing a good segmentation. Illustrate this with the following example: the following figure presents a synthetic image generated by the harmonic equation: $r = \alpha + \beta \cdot \cos(4 \cdot \theta + \gamma)$ and its GVF field. The same synthetic image is again represented with impulsive noise and its GVF field.

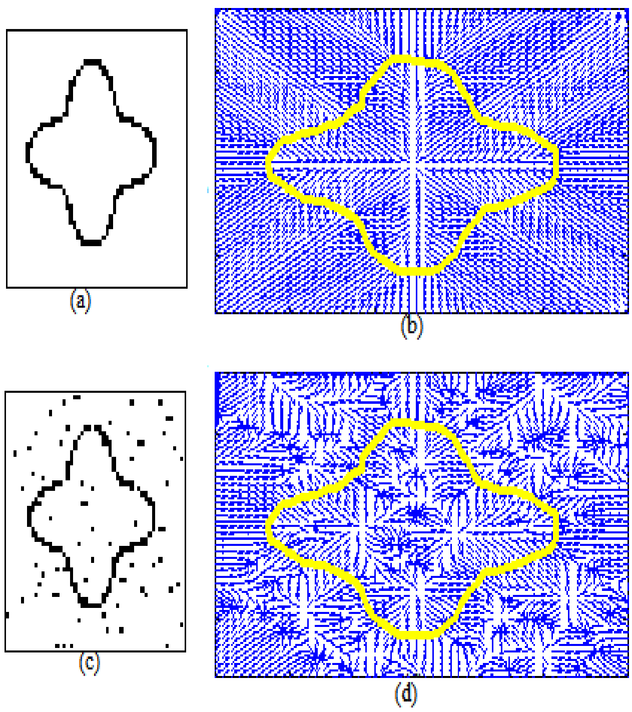


Figure 2: **(a)** synthetic image, **(b)** GVF of (a), **(c)** (a) with impulse noise, **(d)** GVF field of (a)

We can notice that the GVF field in (b) and the GVF field in (d) are different. The noise changes the direction of several vectors of the field, which makes the field messy, and consequently, the attraction of the active contour towards the desired edges becomes difficult.

2) Solution

By inspecting figure 2, we can easily see that if a point of the active contour reached a noise point, it cannot leave it, because all vectors surrounding the noise points head toward these points. Hence, the idea is to shift points of the active contour, so that they no longer coincide with the noise.

To use the previous idea, the active contour must be reparameterized after each iteration of deformation, such a parameterization must be uniform (a same distance between successive points of the active contour). We can make this parametrization as follows: take all points of the active contour $P_i = (x_i, y_i)$, for $i = 0, \dots, n$, introduce $t_0 = 0$ and $t_i = \sum_{k=1}^{i} l_k$ where l_i represents the length of each segment $P_{i-1}P_i$, every t_i represents the cumulative length of the piecewise line that joins the points from $P_0$to P_i. Using the two sets of values $\{t_i, x_i\}$ and $\{t_i, y_i\}$ as interpolation data, we obtain the two splines S_x and S_y, with respect to the independent variable t, that interpolate $x(t)$ and $y(t)$, respectively. The parametric curve $S(t) = (S_x(t), S_y(t))$ is called the cumulative parametric spline, and approximates satisfactorily even those curves with large curvature. Moreover, it can also be proved (see [13]) that it is geometrically invariant. In our approach, we choose a fixed distance between successive points of the active contour after each iteration of deformation, this distance should not be large to well approach the shape, at the same time it should not be small because we want to shift these points to prevent noise points. After that, we perturb these new points by a fixed spacing less than the spacing between two successive points of active contour, these points move together and thus their spacing remains the same.

To compare results, we present the initial active contour by n equidistant points, and then to estimate the accuracy of the results at each iteration, we calculate the number of pixels between the active contour result and the true shape in the image. We use five versions to compare:

a) No perturbation.
b) A perturbation with a fixe gap $s = 2, 3$.
c) A random perturbation at each iteration in the range [0,2], [0,3].
d) A perturbation that maximizes the probability of avoiding the points of noise, i-e, have the highest possible external energy.

The result is:

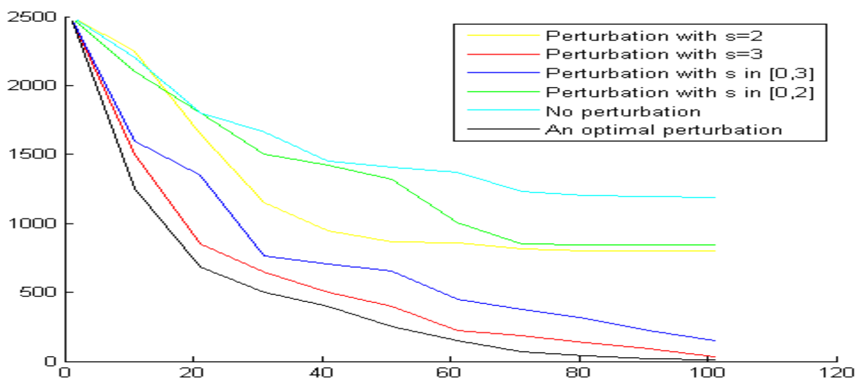
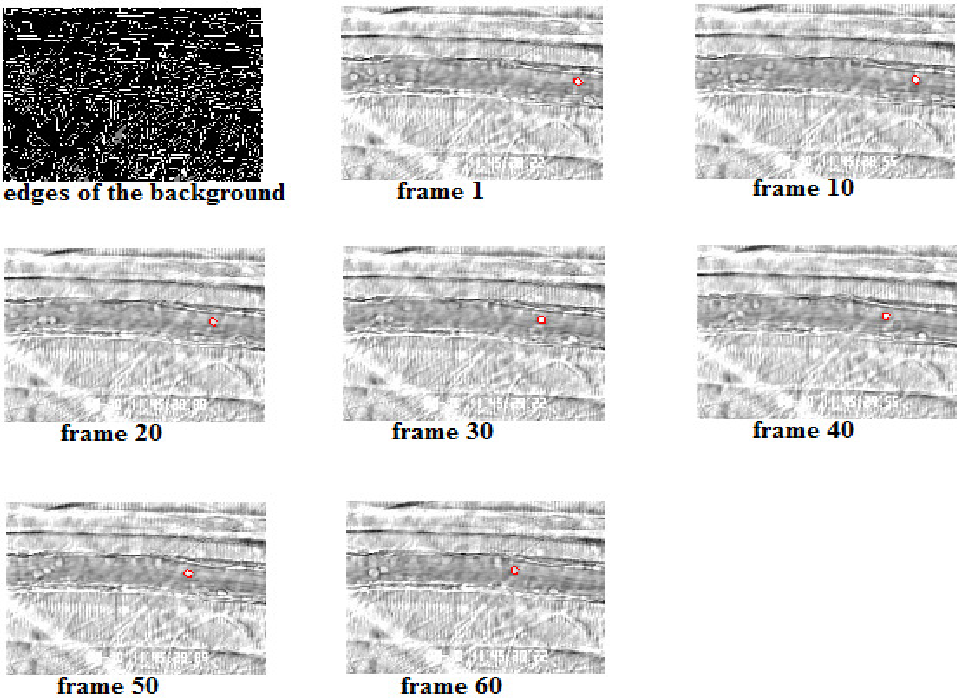


Figure 3: The number of pixels between the active contour result and the true shape at each iteration.

For all cases, the area decrease rapidly from the initial value, but, when the number of iteration becomes large, it levels off. When no perturbation is used, the number of pixels between the snake and the true shape, levels off at a high value. When perturbations were used, the area continues to drop, because there are more possibilities for increasing the energy. We also see that using a fixed gap for the perturbation for all itérations is preferable.

IV. Application in target tracking.

In this section, we show how the proposed parameterization improved the tracking; the snake was used to track a single leukocyte from video sequences, the background where the leukocyte rolling is very noisy. In the first frame, the target is manually selected, and then it is refined by an active contour algorithm. For the following frames, the predicted in the previous frame result is used to initialize the snake.



We see that the proposed algorithm can be used for tracking real-world scenarios and helps to prevent the divergence of the active contour from the target of interest. Note that without the proposed algorithm, the snake is not smooth, develops loops and the tracking result is also flawed.

V. Conclusion

We have proposed a fast and simple approach to overcome the problem of noise for parametric active contours. We have shown that the proposed algorithm is more robust to noise. Using this algorithm we are also able in the presence of noise to track targets in real-world scenarios.

VI. References

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