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Distraction in GVF-based Segmentation

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Abstract— For complex images with the presence of stronger edges near the desired boundary, the snake used in gradient vector flow (GVF)-based segmentation method may be distracted to converge wrongly on the boundary with stronger edges. The factors and conditions which bring about this phenomenon are investigated in detail and the results are described in this paper. Possible solutions to the problem are also presented.

Keywords—GVF, DDGVF distraction, segmentation.

I. INTRODUCTION

Snakes, or active contour models, are some of the most popular methods in image segmentation. Snakes are curves defined within an image domain that move under the influence of internal forces and external forces. Internal forces are designed to smooth the model during deformation. External forces are tasked to move the model toward desired features of the image. There are two key drawbacks associated with snakes introduced by Kass *et al.* [1]. First, the initial position of the snake must be close enough to the desired contour in the image. Otherwise the snake may be trapped in local minima instead of evolving correctly toward the desired contour. Second, poor convergence may result as the snake has difficulty evolving to concavities or sharp corners.

To solve the problem of limited capture range and poor convergence, Xu and Prince proposed *gradient vector flow* (GVF) as a new external force for snakes [2]. As the GVF field is calculated as a diffusion of the gradient vectors of a gray-level or binary edge map derived from the image, it greatly increases the capture range of the snake and its capability to move into boundary concavities. Various improvement of GVF has been proposed for different applications [3]–[6]. In [7], a new type of dynamic external force for snakes named *dynamic directional gradient vector flow* (DDGVF) is proposed. By making use of directional edge information, the DDGVF snake is able to distinguish between positive and negative boundaries for concave shape.

II. THE DISTRACTION PHENOMENON

The GVF field $\mathbf{v}(x, y) = [u(x, y), v(x, y)]$ is defined as the equilibrium solution of the following system of partial differential equations:

$$\mathbf{v}_t = \mu \nabla^2 \mathbf{v} - (\mathbf{v} - \nabla f) |\nabla f|^2, \mathbf{v}_0 = \nabla f \quad (1)$$

where $\mathbf{v}_t$ denotes the partial derivative of $\mathbf{v}$ with respect to t , and ∇^2 is the Laplacian operator. f is an edge map derived from the image and set to have larger values at the features of interest. When $|\nabla f|$ is small, the solution of (1) is dominated

by the term $\mu \nabla^2 \mathbf{v}$, which implies homogeneous linear diffusion yielding a slowly varying field of $\mathbf{v}$. Whereas when $|\nabla f|$ is large, the second term in (1) is dominant and $\mathbf{v}$ becomes close to ∇f . The parameter μ regulates the tradeoff between the first term and the second term in the equation and should be set according to the amount of noise present in the image (larger for higher noise).

As the GVF field (as well as other GVF-based external force) is calculated as a diffusion of the gradient vectors of an edge map derived from the image, it greatly increases the capture range of the snake and its capability to move into boundary. The diffusion process is somehow similar to smooth filtering: the larger the number of iteration (equivalent to larger size of the smoothing kernel), the wider the range of pixels involved.

In the ‘Garbo’ image, her upper lip has a stronger *negative* edge than her left chin [7]. When the GVF method is applied to the image, because of the large capture range, the contour evenly converges (at iteration No.80) to the upper lip as shown in Fig. 1 (a). For want of a better name, we shall refer to this phenomenon as ‘**distraction**’. However, at iteration No.40, the influence from the upper lip is not significant and the detected boundary stays on the chin (Fig. 1 (b)).

To find the ‘correct’ number of iteration for the task, we use manually drawn points along boundary as shown in Fig. 2 as ground truth. Mean boundary errors between the computer-detected boundaries and the ground truth boundaries are then determined as a function of the number of iteration. The results are plotted in Fig. 3.

It can be seen from Fig. 3 that the correct number of iteration for this particular image is 40 when the boundary error is minimum.

III. EXPERIMENTS

Experiments are carried out to explore the distraction phenomenon in detail. For the experiments, a square simulating the face and a rectangle simulating the mouth as shown in Fig. 4 are used.

Four parameters are considered: R (ratio of intensity difference), L (length), H (distance) and $Iter$ (iteration time). The dimensions L , and H are illustrated in Fig. 4. R is the ratio of the intensity differences given by $R = \frac{1-U}{1-0.8}$, where U is the intensity of the rectangle. The intensity values are normalized so that

Fig. 1 Boundaries obtained from DDGVF after (a) 80 iterations and (b) 40 iterations.

Fig. 2 Ground truth points for (a) the chin boundary and (b) the face boundary.

the maximum pixel value corresponds to the intensity of 1. In Fig. 5, the desired square boundary is attracted by a stronger negative edge above when the number of iteration is increased for a given set of R , L and H values

To assess the influence of the parameters, the thresholds of distraction for different R , L , H , and $Iter$ are determined and the results are displayed in Fig. 6. The way to read the Fig. 6 is as follows. For Fig. 6(a), the number of iteration is kept constant at 100. Take the case when $R=2.0$, distraction will not occur when the value of H is above 8 (i.e. when it is far away) regardless of the value of L . For value of H equals to 6, say, the value of L must be equal or above 10 for distraction to take place at 100th iteration. In short, the conditions for distraction to occur are those combinations to the left of the curve for a given value of R .

For Fig. 6(d) where the value of R is kept constant, the number of iterations for distraction to happen is indicated on the curve. The conditions for distraction to happen are also those combinations to the left of the curve.

From the figures, it can be observed that distraction happens only when a nearby edge is stronger than the desired boundary in intensity (large R), sufficiently close by (small H), and sufficiently wide (large L). When all the three conditions are met, the number of iteration should be controlled to prevent the distraction. It can be seen that when H is large, i.e., the strong edge is far from the desired edge, (the red dashed line becomes vertical), the square boundary will not be distracted no matter how large is the number of iteration.

For the Garbo image with gray level of 0 to 255 (white) (resized to 100*100), $R = \frac{(196-42)/255}{(110-73)/255} = 4.16 \approx 4$, $H \approx 13$, $L \approx 18$. Distraction happens when the number of iteration time exceeds 75 (see Fig. 6(d)), which is consistent with the observation in Section 2.

Fig. 3 Mean boundary errors between the computer-detected boundaries and the ground truth boundaries.

IV. POSSIBLE SOLUTIONS

In GVF-based methods, the number of iteration used for the calculation of GVF force is usually set to be proportional to the size of images. Actually the optimal number of iteration or optimal capture range should be large enough to attract the snake without interference from undesired objects nearby. When there are multiple strong edges available in the image, as in the 'Garbo' case above, it is recommended not to overdo the number of iterations. A combination of the method with say edge detection and test of continuity of boundary can be used to determine when to conclude the iteration process.

Another solution is to exclude or blur the unlikely area of search to prevent the occurrence of distraction.

V. CONCLUSION

In this paper, the phenomenon of distraction that can occur when the *gradient vector flow* (GVF)-based segmentation method is used is presented. Such distraction happens when there is a strong edge close to the desired boundary. As a result, when the snake is allowed to carry on searching after the desired boundary is found, it may be distracted the strong edge.

An apparent solution (although not an easy one to implement) is to stop further iteration when the desired boundary is determined. This can be carried out by combining the technique with other edge detection method. Another way to solve the problem is to exclude the unlikely area in the search.

REFERENCES

- [1] M. Kass, A. Witkin, and D. Terzopoulos, "Snakes: Active contour models," *Int. J. Comput. Vis.*, vol. 1, pp. 321–331, 1988.
- [2] C. Xu and J. L. Prince, "Snakes, shapes, and gradient vector flow," *IEEE Trans. Image Process.*, vol. 7, no. 3, pp. 359–369, Mar. 1998.
- [3] C. Xu and J. L. Prince, "Generalized gradient vector flow external forces for active contours," *Signal Process.*, vol. 71, pp. 131–139, 1998.
- [4] M. Wei, Y. Zhou, and M. Wan, "A fast snake model based on nonlinear diffusion for medical image segmentation," *Comput. Med. Imag. Graph.*, vol. 28, pp. 109–117, 2004.
- [5] N. Paragios, O. Mellina-Gottardo, and V. Ramesh, "Gradient vector flow fast geometric active contours," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 26, no. 3, pp. 402–407, Mar. 2004.
- [6] J. Tang, S. Millington, S. T. Action, J. Crandall, and S. Hurwitz, "Ankle cartilage surface segmentation using directional gradient vector flow snake," in *Proc. Int. Conf. Image Processing*, 2004, pp. 2745–2748.
- [7] J. Cheng and S-W. Foo, "Dynamic Directional Gradient Vector Flow for Snakes," *IEEE Trans. Image Process.*, vol. 15, no. 6, pp. 1563–1571, Jun. 2006.

Fig. 4 H is the distance of the rectangle from the desired edge and L is the length of the rectangle, both in number of pixel. R is the ratio of the intensity differences given by $R=(1-U)/(1-B)$, where U and B are respectively the normalized intensities of the rectangle and the background. The intensity values are normalized so that the maximum pixel value has an intensity of 1.0. For the three images, the normalized intensity of the background B is 0.8.

Fig. 5 (a) Original image of 100×100 with $R = 2.0$, $H = 6$, and $L = 20$. (b) Boundary obtained from DDGVF after 25 iterations. (c) Boundary after 50 iterations when distraction happens.

(a) Number of iteration set at 100

(b) R set at 1.5

(c) R set at 2.0

(d) R set at 4.0

Fig. 6 Threshold of distraction for different combinations of R , L , and H . Distraction happens for combinations of parameters to the left of the red dashed lines.