Image Segmentation Using Active Contour Model

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Abstract:
Image segmentation is one of the substantial techniques in the field of image processing. It is vastly used for medical purposes , tracking growth of tumor for surgical planning and simulation. Active contours or snakes are used extensively for image segmentation and processing applications, particularly to locate object boundaries. Active contours are regarded as promising and vigorously researched model-based approach to computer assisted medical image analysis. However, its utility is limited due to poor convergence of concavities and small capture range. This paper shows the application of an external force that largely solves both problems. This external force is called gradient vector flow (GVF). Using several examples to show that, GVF because of its large capture range moves snakes into boundary concavities.

Keywords: *Active contour models, edge detection, gradient vector flow, image segmentation, snakes*

1. Introduction

Breaking an image into its constituents is called segmentation, which basically means separating the background and foreground. Active contours [1] or snakes provide an effective way of segmentation [2] of curves defined within the image domain that can move under the influence of external and internal forces. These forces are defined such that the snake will shrink wrap to an object boundary. This method is widely used in many applications, including motion tracking, edge detection and segmentation.

Active contours are extensively used in the field of digital image processing to find the contour of an object by forming a snake around its boundary. It involves running a low level image processing task such as canny edge detection which is mostly unsuccessful because often the edge is not continuous, i.e. the image might be noisy or there might be concavities present in the image. Hence Active Contours are an advanced way of image segmentation as it adds certain properties to the image before performing segmentation which makes the process of locating the boundary comparatively easier .

The major problem that was encountered in the traditional snake model was that the initial contour must in general, be close to the true boundary or else it will predict an incorrect result as shown in figure 1. Most of the methods that are proposed to solve the above problems are ineffective in solving this issue and end up creating more difficulties.

In this paper we present a class of external force for active contour model that answers both the problems mentioned above. This external force, which we call gradient vector flow (GVF)[5], is computed as a diffusion of the gradient vectors of a gray-level or binary edge map derived from the image. The resultant field has a large capture range and forces active contours into concave regions, hence solving both the problems. Since the external forces cannot be written as the negative gradient of a potential function, GVF snake is different from all other snake models used before. The major advantages of GVF snake over the other snake models are its intensity for initialisation and its ability to move into concavities. The GVF snake can be initialized far from the boundary since it has a large capture range. And unlike pressure forces, the GVF snake does not require prior knowledge about when to shrink or expand towards the boundary.

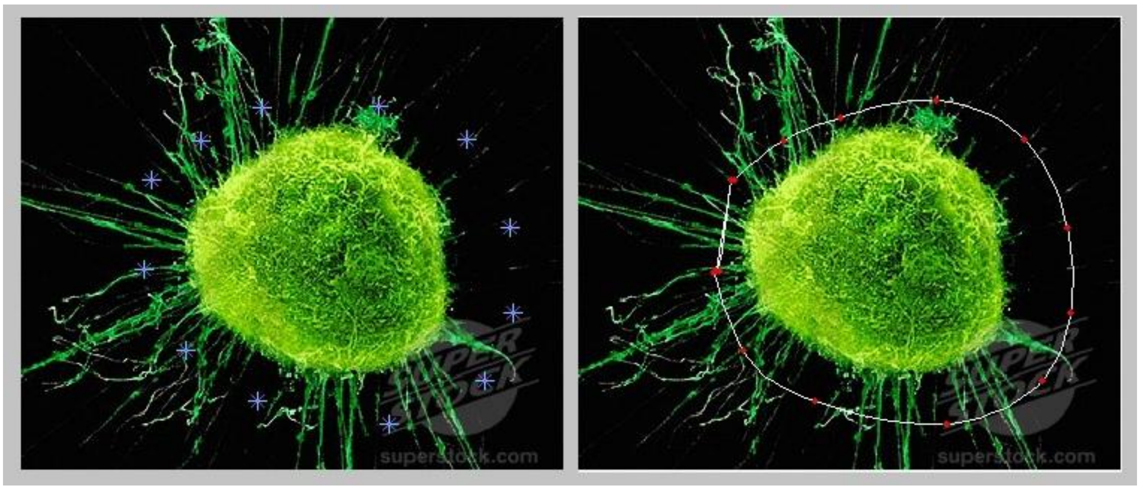

Fig1. Shows that major drawback of traditional active contour model i.e. small capture range

2. Literature Survey

2.1. *Original Snake Model by Kass*

The concept of active contours was introduced by Kass, in the seminal paper "Snakes: Active Contour Models " [Kass-88]. The paper was extremely influential and has since then been a major topic for research As we have already discussed a snake is a parametric curve which tries to move into a position where its energy is minimized. Kass et al. introduced the following energy functional for calculating the snake energy.

$$E_{snake} = E_{internal} + E_{external} + E_{constraint}$$

The snake energy consists of three terms. The first term E_{int} represents the internal energy of the snake while the second term E_{img} denotes the image forces, the last term Econ gives rise to external constraint forces. The sum of the image forces E_{img} and the external constraint forces Econ is also simply known as the external snake forces, denoted by E_{ext}

Internal Energy (E_{int}) depends on the intrinsic properties of the curve and is the sum of elastic energy and bending energy

$$E_{int} = E_{elastic} + E_{bending} = \int_s \frac{1}{2}(\alpha |v_s|^2 + \beta |v_{ss}|^2) ds$$

External energy (E_{ext}) of the contour is derived from the image so that it takes on its smaller values at the function of interest such as boundaries. Define a function $E_{image}(x,y)$ so that it takes on its smaller values at the features of interest, such as boundaries

$$E_{ext} = \int_s E_{image}(v(s)) ds$$

3. Gradient Vector Flow Model (GVF)

As discussed earlier one of the major problems faced during the implementation of active contour model was the poor convergence of this snake, this is because the forces point horizontally in opposite direction. Another weakness of the traditional snake model is that it has a limited capture range as seen in figure 1, this can be explained by the simple theory that the magnitudes of the external forces die out quite rapidly away from the object boundary. The boundary localization will become less accurate and distinct. To overcome this problem we introduce the GVF snake model.

The gradient vector flow snake is used in order to increase the capture range and improve the snakes ability to move into boundary concavities. The capture range of the original snake is generally limited to the vicinity of the desired contour. Furthermore the original snake has problems with moving into concave regions e.g. moving into the concave region of an U-shaped object, the gradient vector flow snake handles these problems by introducing a new external force. By minimizing an energy function we can derive a new vector field by using this external. We call these vector field as gradient vector flow fields

Gradient Vector Flow:- The GVF field is defined to be a vector field

$$\mathbf{V(x,y)} = (u(x,y), v(x,y))$$

Force equation for GVF snake is, $\alpha v_{ss} - \beta v_{ssss} + V = 0$

V(x,y) is defined such that it minimizes the energy functional,

$$E = \iint \mu(u_x^2 + u_y^2 + v_x^2 + v_y^2) + |\nabla f|^2 |V - \nabla f|^2 \, dxdy$$

f(x,y) is the edge map of the image.

The above equations are solved iteratively using time derivative of u and v. These equations provide further intuition behind the GVF formulation. We note that in the homogenous region the second term in both regions is zero because the gradient of f(x, y) is zero.

After the application of the GVF snake model we can see that the snake can move towards object that are too far away from the boundary. Secondly, that now snakes can move into boundary concavities. Hence we can conclude that both the problems of the traditional snake models have been successfully resolved

4. Greedy Snake Algorithm

A greedy algorithm makes locally optimal choices, hoping that the final solution will be globally optimum. It is a feature extraction technique widely used in image segmentation. It works like a elastic band being stretched around and object and then being released. Initial points defined around feature to be extracted explicitly defined and the Pre-defined number of points are generated.

Points are calculated by an **Iterative Process:**

- Energy function for each point in the local neighborhood is calculated
- The point is moved to the next point with lowest energy function
- This process is repeated for every point
- Iteration is done until termination condition met
- Defined number of iterations
- Stability of the position of the points

The final step in the iteration of the greedy snake algorithm consists of checking whether the number of points moved in the iteration is below the threshold . This is used as a stopping criterion as the snake is presumed to have reached minimum energy when most of the control points have stopped moving.

5. Results and Discussion

The application of GVF to the traditional active contour model introduced by Klass significantly improves the quality and accuracy of image segmentation. The major problem that was encountered was that of the small capture range, this is eliminated by using the external force supplied by the gradient vector

In Fig 2 and Fig 3 we can see the different stages of segmentation for a cancer cell. First step involves localization of the object i.e. forming a rough outline along the boundary of the object. Next it moves through an iterative process and finds the boundary of the tumor

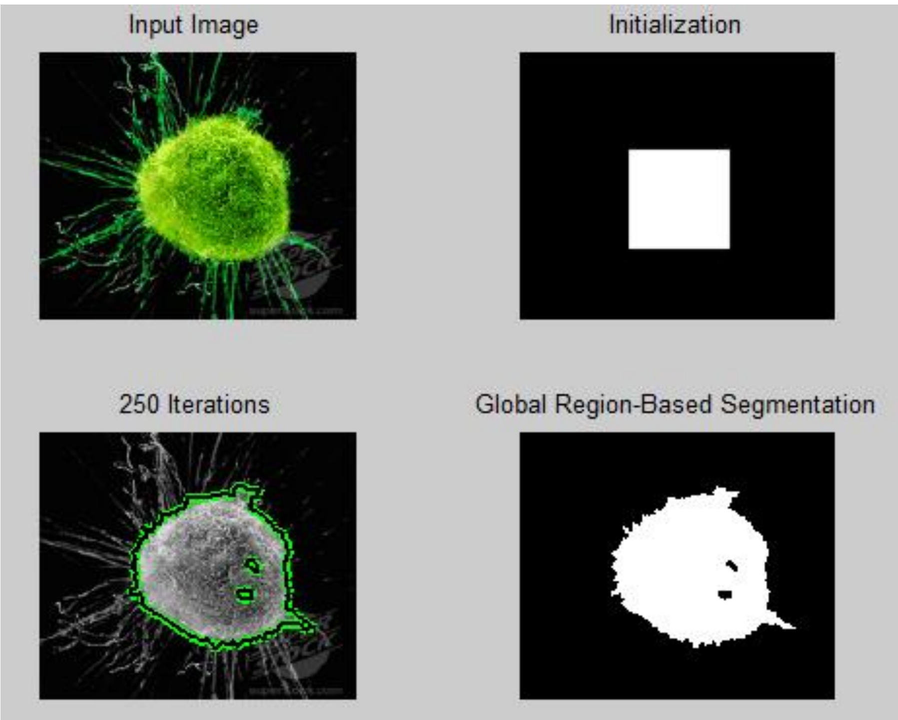

Fig 2. Stages of image segmentation for a cancer cell present in the lung

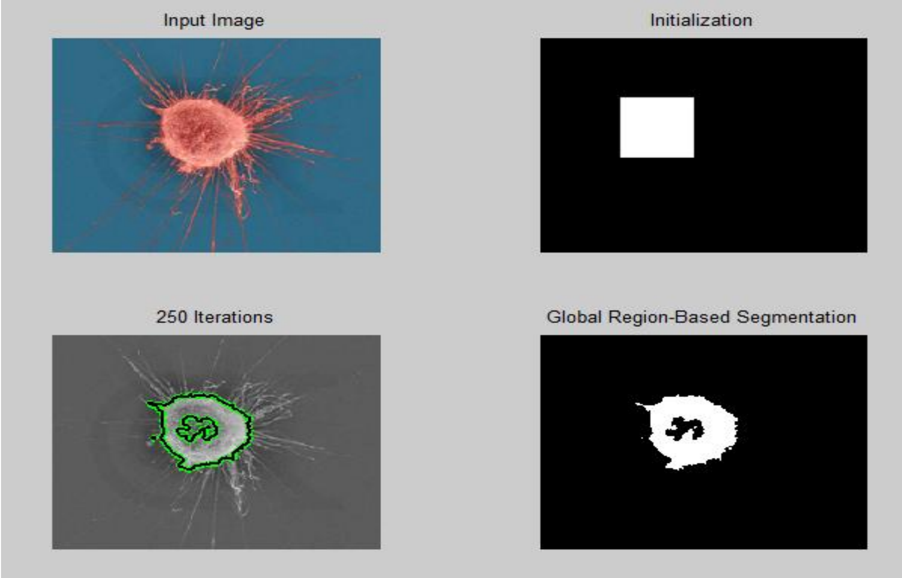

Fig 3. Stages of image segmentation of breast cancer cell

6. Conclusion

The complexity and variability of anatomic structures, poses many challenging problems for computer vision community in search for a good segmentation model. Snakes have proven to be very attractive approach and have produced good results in many medical imaging applications. We have successfully applied the Gradient Vector Flow (GVF) model. This new external force model for active contours successfully allows convergence to boundary concavities and also provides a large capture range for the snake. GVF model provides a collective way of treating visual problems that were till now treated differently. We can also conclude that although the GVF snake model is slower than the traditional snake model it is much more accurate. However, continued development, improvement and refinement of these methods is an important research area with the goal of producing automated, accurate and robust segmentation models

7. References

[1] W.F. Ames. Numerical Methods for Partial Differential Equations. Academic Press, 1977.

[2] R. Aris. Discrete Dynamic Programming. Blaisdel, 1964.

[3] D.R. Bailes and C.J. Taylor. The Use of Symmetry Chords for Expressing Grey Level Constraints. In Proc. British Machine Vision Conference, pages296-305. Springer, 1992.

[4] D.H. Ballard. Generalizing the Hough Transform to Detect Arbitrary Shapes. Pattern Recognition, 13:111-122, 1981.

[5] R. Bellman. Dynamic Programming. Princeton University Press, 1957.

[6] A. Blake and M. Isard. Active Contours. Springer, 1998.

[7] G.J. Borse. Numerical Methods with Matlab. PWS, 1997.

[8] J.P Boyd. Chebyshev and Fouirer Spectral Methods. Springer, 1985.

[9] W. Cheney and D. Kincaid. Numerical Mathematics and Computing. Brook-s/Cole, 1985.

[10] J.H. Chuang. Potential-Based Approach for Shape Matching and Recognition. Pattern Recognition, 29:463-470, 1996.

[11] P.G. Ciarlet and J.L. Lions. Handbook of Numerical Analysis, Volume 5. El-sevier, 1997.

[12] L.D. Cohen. NOTE On Active Contour Models and Balloons. Computer Vision and Image Processing: Image Understanding, 53:211-218, March 1991.

[13] L.D. Cohen and I.Cohen. Finit-Element Methods for Active Contour Models and Baloons for 2-D and 3-D Images. IEEE Transactions on Pattern Analysis and Machine Intellingence, 15:1131-1147, November 1993.

[14] C. de Boor. A Practical Guide to Splines. Springer, 1978.

[15] A. Chakraborty et.al. Deformable boundary finding influenced by region homogeneity. Available at the web site of the Yale University, March 1994.

[16] A.A. Amini et.al. Using Dynamic Programming for Solving Variatinal Problems in Vision. IEEE Transactions on Pattern Analysis and Machine Intelligence, 12:855-867, September 1990.

[17] A.K. Jain et.al. Object Matching Using Deformable Templates. IEEE Transactions on Pattern Analysis and Machine Intelligence, 18:267-278, March1996