

VARIOUS ACTIVE CONTOUR MODELS

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ABSTRACT: *One of the substantial techniques in the field of digital image processing is image segmentation. It is excessively used in the field of medicine provides visual means for identification, inspection and tracking of diseases for surgical planning and simulation. Active contours or a snake is an image segmentation technique which is widely used for boundary detection. They are regarded as promising and vigorously researched model-based approach to computer assisted medical image analysis. However, its utility is limited due some problems caused in the traditional methods, i.e. Poor convergence of concavities and small capture range. This paper shows the application a new model for active contours, which comprises of the Balloon Model and the Greedy model. This model helps in improving the detection quality of closed edges, thereby resolving the limitations of the traditional snake model.*

Keywords— *Active contour models, balloon model, edge detection, greedy snake*

I: INTRODUCTION

Segmentation is the process of splitting the image into several parts like objects (also called foreground or background). 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.

There are two types of active contour models in literature today: - *parametric active contours and geometric active contours* [3][4]. Our main focus here is on parametric contours. Parametric active contours synthesize parametric curves within an image domain and allow them to move towards desired features, usually edges. Typically the curves are drawn towards the edges by potential forces, which are defined to be the negative gradient of a potential function. Additional forces like the potential forces and pressure forces together comprise the external forces. There are also internal forces designed to hold the curve together (elastic forces) and to keep it from bending too much (bending forces).

There are two main difficulties we face during the parametric active contour algorithm. First, the active contours have difficulties progressing into boundary concavities. The second problem is that the initial contour must in general, be close to the true boundary or else it will predict an incorrect result. Most of the

methods that are proposed to solve the above problems are ineffective in solving both issues and end up creating more difficulties.

In this paper we present two distinct models to help resolve the problems mentioned above. Firstly, the *balloon model* or the expanding snake model helps resolve the problem of small capture range. When the approximate boundary of an object is unknown the traditional model fails to provide accurate results, in such situations using the balloon model shows robustness. Secondly, the *gradient vector flow* (GVF) model [5] which forces active contours into concave regions. GVF is computed as a diffusion of the gradient vectors of a gray-level or binary edge map derived from the image. 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 using these models over the traditional model are that it can be initialized far from the boundary since it has a large capture range. And unlike pressure forces, it does not require prior knowledge about when to shrink or expand towards the boundary.

II: LITERATURE SURVEY

A. Parametric snake model

The contour [1] is defined in the (x, y) plane of an image as a parametric curve

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

Contour is said to possess energy (E_{snake}) which is defined as the sum of the three energy terms.

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

The energy terms are defined cleverly in a way such that the final position of the contour will have a minimum energy (E_{min}). Therefore our problem of detecting objects reduces to an energy minimization problem.

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

Elastic Energy ($E_{elastic}$) of the curve is treated as an elastic rubber band possessing elastic potential energy. It discourages stretching by introducing tension.

$$E_{elastic} = \frac{1}{2} \int_s \alpha(s) |v_s|^2 ds \quad v_s = \frac{dv(s)}{ds}$$

Weight $\alpha(s)$ allows us to control elastic energy along different parts of the contour consider to be constant α for many applications.

Bending Energy ($E_{bending}$): The snake is also considered to behave like a thin metal strip giving rise to bending energy. It is defined as sum of squared curvature of the contour.

$\square(s)$ plays a similar role to $\alpha(s)$. Bending energy is minimum for a circle.

Total internal energy of the snake can be defined as:-

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

$$E_{bending} = \frac{1}{2} \int_s \beta(s) |v_{ss}|^2 ds \quad v_{ss} = \frac{d^2v(s)}{ds^2}$$

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.

Key rests on defining $E_{image}(x,y)$.

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

Energy and force equations: The problem currently on hand is to find a contour $v(s)$ that minimize the energy functional

$$E_{snake} = \int_s \frac{1}{2} (\alpha(s) |v_s|^2 + \beta(s) |v_{ss}|^2) + E_{image}(v(s)) ds$$

Using variational calculus and by applying Euler-Lagrange differential equation we get following equation

$$\alpha v_{ss} - \beta v_{ssss} - \nabla E_{image} = 0$$

Equation can be interpreted as a force balance equation.

$$F_{int} + F_{image} = 0 \quad F_{ext} = -\nabla E_{image}$$

Each term corresponds to a force produced by the respective energy terms. The internal force F_{int} discourages stretching and bending while the external potential force F_{image} pulls the snake toward the desired image edges.

Solving the Euler equation:-
Consider the snake to also be a function of time i.e. $v_t(s,t)$

$$\alpha v_{ss}(s,t) - \beta v_{ssss}(s,t) - \nabla E_{image} = v_t(s,t)$$

$$v_t(s,t) = \frac{\partial v(s,t)}{\partial t}$$

If RHS=0 we have reached the solution. On every iteration update control point only if new position has a lower external energy. Snakes are very sensitive to a false local minimum which leads to wrong convergence.

B. Weakness of Traditional Snakes

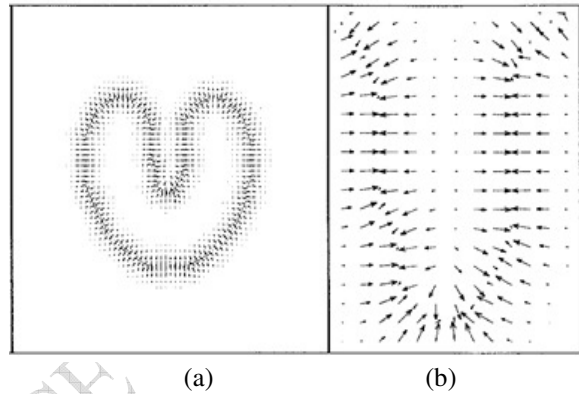


Fig. 1 (a) traditional potential forces and (b) close-up

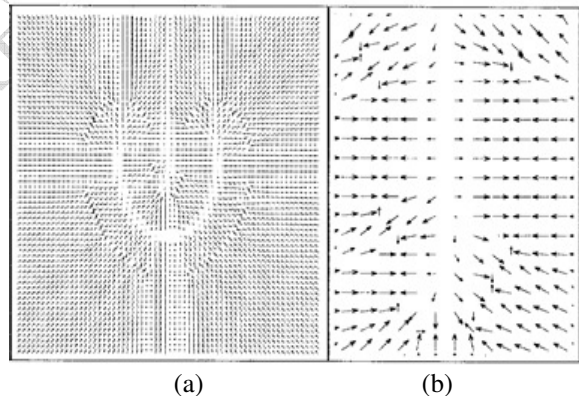


Fig. 2 (a) traditional distance forces and (b) close-up
The reason for the poor convergence of this snake as seen in fig. 1(b) is because the forces point horizontally in opposite direction. Another weakness of the traditional snake model is that it has a limited capture range; this can be explained in fig. 1(b). The magnitudes of the external forces die out quite rapidly away from the object boundary. The boundary localization will become less accurate and distinct.

External forces are a negative gradient of a potential function that is computed using Euclidean distance map. These forces are referred to as distance potential forces so as to distinguish them from traditional potential forces. The distance potential forces shown in fig. 2(a) have vectors with large magnitudes away from the object, explaining why the capture range is large for external force model. In fig.2 (b) the traditional potential forces are horizontally in

opposite direction, which pulls the snake apart and not downward into the boundary concavity. Hence the problem of convergence is not solved by distance potential forces.

III: Balloon Model

The snake model originally introduced by Kass has been further developed by modified in recent years. The balloon model or the expanding snake mode [6] is one of the examples of this. Unlike, the traditional snake that shrinks wraps to the image boundary, this snake model expands outwards.

This model is based on an additional inflation force applied to give stable results. A snake which is not close to contours is not attracted by them. The curve behaves like a balloon which is inflated. When it passes by edges, will not be trapped by spurious edges and only is stopped when the edge is strong. The initial guess of the curve not necessarily is close to the desired solution. Pressure force is added to the internal and external forces.

The expansive behavior is achieved by modifying the values of f_x ; f_y as followed,

$$f_x(x, y) = k_1 n(s) - k \frac{\nabla P_x}{\|\nabla P_x\|}$$

$$f_y(x, y) = k_1 n(s) - k \frac{\nabla P_y}{\|\nabla P_y\|}$$

where $n(s)$ is the unit principal normal vector to the curve at point $v(s)$, and k_1 is the amplitude of this force. k_1 and k are chosen such that they are of the same order, which is smaller than a pixel size and k is slightly larger than k_1 so an edge point can stop the Inflation force. The curve then expands and it is attracted and stopped by edges as before. The smoothing effect with the help of the inflation force then removes the discontinuity and the curve then passes through the edge.

IV: Greedy Snake

The greedy snake algorithm was introduced by Williams and Shah their approach differs from the original Kass et al. snake and the balloon snake by computing the movement of the snake points in a fully discrete manner. This entails computing the movement of each snake point individually on the discrete indices of the image, as opposed to computing the iteration of the whole snake at once as with the Kass et al. algorithm. The movement of each snake point is computed by looking at the neighbourhood of pixels around the snake point and then moving the snake point to the position in the neighbourhood which minimizes the energy term. The name of the greedy algorithm is derived from the way the snake points choose their new positions.

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.

V: Results and Discussion

With the help of traditional snake we can find the boundary of an image object. But there are several disadvantages for this.



Fig 1. Original Image of head CT

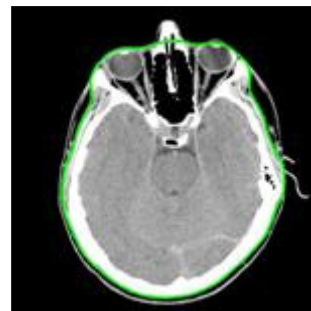


Fig 2. Output Image using traditional snake

Here we can see that the traditional snake is less sensitive to curvature, so the curvature is left out at the top in the image.



Fig 3. Original Image of map



Fig 4. Output Image using traditional snake

Here we can see that the traditional snake is less sensitive to weak edges, so it leaves out some portion of the map at the bottom and at the left upper portion of the map.



Fig 5. Sobel edge operated image cell



Fig 6. Output Image with balloon model iteration 45

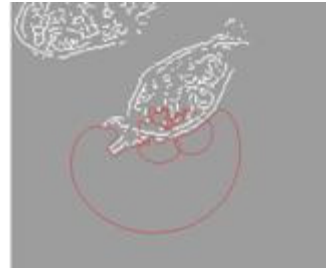


Fig 7. Output Image with balloon model iteration 69

By using Balloon model it increases the capture range of the snake but it has the problem of broken edge. Because of noise or some property of an object to background all edge detection operators produce broken edge. This creates several problems for detecting the boundary of objects. These discontinuities in edge should be removed by edge linking procedure but they also have somewhat limitations.

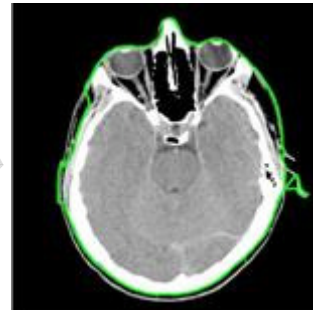


Fig 8. Output Image of head CT using Greedy snake



Fig 9. Output Image of map using Greedy snake

By using Greedy snake we see that it is sensitive to curvature as seen in Fig 8 and it is sensitive to weak edges also. Here in Fig 9 we see that it includes the two islands in the map. So Greedy snake is better than other discussed here in case of curvature and weak edges.

VI: CONCLUSION

We have successfully reviewed the three distinct snake models i.e. traditional snake model, balloon snake model and the Greedy snake model by applying them to different images and studied their result. Different models provide varied accuracy based on the type of images. Firstly, the

Balloon Model which enables us to give an initial guess of the curve which in turn helps us to deal with the problem of small capture range. Similarly we encounter wide-ranging types of images for segmentation, specially in medicine where cancer cells vary in structure depending upon their location. Hence we can conclude that a combination of these models would provide a robust and comprehensive method for segmentation for various types of images.

REFERENCES

- [1] M. Kass, A. Witkin, and D. Terzopoulos, "Snakes: Active contour models," *Int. J. Comput. Vis.*, vol. 1, pp. 321-331, 1987.
- [2] H. Tek and B. B. Kimia, "Image segmentation by reaction-diffusion bubbles," in *Proc. 5th Int. Conf. Computer Vision*, 1995, pp. 156-162.
- [3] V. Caselles, F. Catte, T. Coll, and F. Dibos, "A geometric model for active contours," *Numer. Math.*, vol. 66, pp. 1-31, 1993.
- [4] R. Malladi, J. A. Sethian, and B. C. Vemuri, "Shape modeling with front propagation: A level set approach," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 17, pp. 158-175, 1995.
- [5] F. Leymarie and M. D. Levine, "Tracking deformable objects in the plane using an active contour model," *IEEE Trans. On Pattern Anal. Machine Intell.*, 15(6):617-634, 1993.
- [6] L. D. Cohen and I. Cohen, "Finite-element methods for active contour models and balloons for 2-D and 3-D images," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 15, pp. 1131-1147, Nov. 1993.
- [7] C. Davatzikos and J. L. Prince, "Convexity analysis of active contour models," in *Proc. Conf. Information Science and Systems*, 1994, pp. 581-587.
- [8] J. L. Prince and C. Xu, "A new external force model for snakes," in *Proc. 1996 Image and Multidimensional Signal Processing Workshop*, pp. 30-31.
- [9] M. Sonka, V. Hlavac, and R. Boyle, *Image Processing, Analysis, and Machine Vision*. Thomson-Engineering, 2007.
- [10] L. D. Cohen, "On active contour models and balloons." *CVGIP: Image Understanding*, 53(2):211-218, Mar. 1991.
- [11] D. Terzopoulos and K. Fleischer, "Deformable models." *The Visual Computer*, 4:306-331, 1988.
- [12] C. Xu and J. L. Prince, "Snakes, shapes, and gradient vector flow," *Technical Report JHU-ECE TR96-15*, The Johns Hopkins University, Oct. 1996.
- [13] J. L. Prince and C. Xu, "A new external force model for Snakes," in *Image and Multidimensional Signal Processing Workshop*, pages 30-31, 1996.
- [14] C. Davatzikos and J. L. Prince, "An active contour model for mapping the cortex," *IEEE Trans. on Medical Imaging*, 14(1):65-80, Mar. 1995.

[15] A. K. Jain, *Fundamentals of digital image processing*. Upper Saddle River, NJ, USA: Prentice-Hall, Inc., 1989.