Application of Kass' Snake in Medical Images Segmentation

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Abstract

A snake is an energy-minimizing spline guided by external constraint forces and influenced by image forces that pull it toward features such as lines and edges. Snakes are active contour models: they lock onto nearby edges, localizing them accurately. Snakes provide a unified account of a number of visual problems, including detection of edges, lines, and motion tracking. We have used snakes successfully for segmentation, in which user-imposed constraint forces guide the snake near features of interest (anatomical structures). Magnetic Resonance Image (MRI) data set and Ultrasound images are used for our experiments. Good results are obtained, where Kass' snake could successfully segment the anatomical structures from MRI and ultrasound images.

Introduction

Techniques of image processing are more and more used in medical field. Mathematical algorithms of feature extraction, modeling and measurement can be exploited in the images to detect pathology, evolution of the disease, or to compare a normal subject to abnormal one. The advance of medical imaging devices has realised several developments in modern medicine and most of them in magnetic resonance imaging: MRI. These techniques provide detailed, non-invasive diagnosis of most human body structures. A second development have provided by coupling some computational techniques to help specialists to analyze the enormous amount of data contained in medical images. The aim of these methods is extracting and analyzing scientifically relevant and clinically important pieces of information from the original set of images.

One of the most important applications is, hence, the segmentation of specific structures. These methods make possible the application of mathematical or geometrical models on the steps of description and analysis of the acquired information. Image segmentation is a fundamental issue in biomedical imaging area. Segmenting structures from medical images and the reconstruction of a compact analytic representation of these structures is difficult. This difficulty was due to the sheer size of the data sets and the complexity and variability of the anatomic shapes of interest. The active contour method is one of the most successful image segmentation techniques; it has received a tremendous amount of attention in medical image processing. The segmentation operation can carried out manually or automatically. A manual segmentation requires a skilled operator trained to use a digital tool to mark the contours of the desired structures. An obvious disadvantage is that an exhaustive process, where the results are hardly repeatable. Automatic techniques usually apply evolving interfaces dynamically adaptable to the desired features contained in the image. The difference between the two techniques is whether or not the user is involved the process (1). In this work, we are mainly concerned about the application active contour model in medical image segmentation.

Kass' Snake Model

Snake model was developed by Kass, Witkin, and Terzopoulos in 1987 (2, 3). The name "snake" was named after its behavior on an image. While minimizing their energy, it slithers on the image.

A snake is expressed as a planar parametric curve in equation [1]. The parameter s is snake control points that are linked together to form it. The snake is not a method to automatically detect the boundary of the desired object in an image. It requires appropriate parameters setting and initial locations of the control points according to the subjective boundary. Therefore, some prior knowledge about the image is required from higher-level system.

$$x(s) = [x(s), y(s)] \quad s \in [0,1] \qquad \text{..........} [1]$$

A snake moves through the spatial domain of an image to minimize the energy functional:

$$E = \int_0^1 \frac{1}{2}\left[\alpha\left|\mathbf{x}'(s)\right|^2 + \beta\left|\mathbf{x}''(s)\right|^2\right] + E_{\text{ext}}(\mathbf{x}(s))\,ds \qquad \text{..........} [2]$$

where α and β are weighting parameters that control the snake's tension and rigidity, respectively, $\mathbf{x}'(s)$ and $\mathbf{x}''(s)$ denote the first and second derivatives of x(s) with respect to s.

The external energy function E_{ext} is derived from the image so that it takes on its smaller values at the features of interest, such as boundaries. Given a gray-level image I(x, y), viewed as a function of continuous position variables (x, y), typical external energies designed to lead a snake toward step edges are:

$$E_{ext}(x, y) = -\left|\nabla I(x,y)\right|^2 \qquad \text{..........} [3]$$

$$E_{ext}(x, y) = -\left|\nabla\left[G_\sigma(x,y) * I(x,y)\right]\right|^2 \qquad \text{..........} [4]$$

where $G_\sigma(x,y)$ is a two-dimensional Gaussian funcuon wiui siauuard deviation σ and ∇ is the gradient operator. If the image is a line drawing (black on white), then appropriate external energies include:

$$E_{ext}(x, y) = I(x, y) \qquad \text{..........} [5]$$

$$E_{ext}(x, y) = G_\sigma(x,y) * I(x,y) \qquad \text{..........} [6]$$

It is easy to see from these definitions that larg
the boundaries to become blurry. Such large σ's are often necessary, however, in order to increase the capture range of the snake.

A snake that minimizes E must satisfy the Euler equation

$$\alpha\, x''(s) - \beta\, x''''(s) - \nabla E_{ext} = 0$$

This can be viewed as a force balance equat .... [7]

$$F_{int} + F_{ext} = 0 \qquad \text{.......... [8]}$$

where $F_{int} = \alpha x''(s) - \beta x''''(s)$ and $F_{ext} = -\nabla E_{ext}$. The internal force F_{int} discourages stretching and bending while the external potential force F_{ext} pulls the snake toward the desired image edges.

To find a solution to [7], the snake is made dynamic by treating x as function of time t as well as S (i.e., x(s, t)). Then, the partial derivative of x with respect to t is then set equal to the left side of [7] as follows:

$$x_t(s, t) = \alpha x''(s,t) - \beta x''''(s,t) - \nabla E_{ext}$$

When the solution x(s, t) stabilizes, the term $x_t(s, t)$ vanishes and we achieve a solution of [7] (2). A solution to [9] can be found by discretizing the equation and solving the discrete system iteratively.

Numerical Methods for Kass' Approach

In the below, there are numerical methods to describe Kass' snake model (2).

- Represent the curve with a set of n points

$$r_i = (x_i, y_i), \quad i = 0, \ldots, n-1$$

- The energy equation can be rewritten as follows:

$$Esnake = \sum_{i=1}^{n} Eint\,(i) + Eext\,(i) \qquad \text{.......... [10]}$$

- According to E_{int}

$$E_{int} = (\alpha(s)\,|r_s(s)|^2 + \beta(s)\,|r_{ss}(s)|^2)/2$$

the derivatives can be approximated with finite differences and are converted to vector notation with $r_i = (x_i, y_i)$, we rewrite E_{int} to $E_{int}(i)$

$$E_{int}(i) = \alpha_i\,|r_i - r_{i-1}|^2/2 + \beta_i\,|r_{i-1} - 2r_i + r_{i+1}|^2/2$$

where r (0) = r (n).

- The corresponding Euler equations is:

$$\alpha_i (r_i - r_{i-1}) - \alpha_{i+1} (r_{i+1} - r_i) + \beta_{i-1}(r_{i-2} - 2r_{i-1} + r_i)$$
$$-2\beta_i(r_{i-1} - 2r_i + r_{i+1}) + \beta_{i+}\ {}_{5}\ - 2r_{i+1} + r_{i+2})$$
$$-(f_x(i), f_y(i)) = 0 \qquad \text{.......... [11]}$$

where

$$f_x(i) = -\partial E_{ext} / \partial x_i$$

$$f_y(i) = -\partial E_{ext} / \partial y_i$$

Kass' Snake Algorithm

Algorithm of Kass' snake is shown in the Fig (1).

Implementation of Kass' Snake

The implementation of Kass' snake algorithm involves loading the image, giving an initial snake by user, inputting the values of alpha, beta and the number of iteration, and then performing the snake algorithm. The Kass' snake algorithm was implemented on line drawing images, gray level images, and series of gray level images.

Line Drawing Images

An implementation of the Kass' snake algorithm was first run on a line drawing 256 × 256 pixel image containing a Circle object as shown in Fig (2). As can be seen from the outputs, the algorithm correctly converges to the object boundary. The algorithm was next run on a line drawing 256 ×256 pixel image containing a convex polygon. The results can be seen in Fig (3). The snake succeeded in converging to the boundary positions in this example too. The values of Kass' snake parameters of the two examples are shown in table (1).

Gray Level Images

In this section we show how the Kass' snake, can be applied to medical image segmentation. In order to show the interests of the segmentation by Kass' snake, we select an MR image of 256×256 pixels. The image represents slice liver attained of a hepatic cystic lesion.

In order to segment the pathology in liver slice image, we must proceed initially by an operation of pretreatment; this consists of application of the Gaussian filter to the initial image. The edge map was computed by using the Gradient operator as mentioned before. As shown in Fig (4), the edge map shows higher values where the image gradient is larger, and low values over homogeneous regions. The Gaussian filter blurs the edges, thus increasing the snake capture range as it spreads the force vectors along the potential field. Using a Kass' snake model and a fair initial position, we can see that it correctly evolves towards the desired boundary, see Fig (5), The values of snake parameters are shown in table (2).

Also we used Kass' snake model to segment the embryo from Ultrasound image. Kass' snake could correctly evolve towards the desired boundary of embryo, see Fig (6). The values of snake parameters are shown in table (2).

Application to Multiple Slices

The graphical user interface (GUI) of the program has the ability to save the current snake, then to reload it for use on the same image or other images. Therefore, the snake can be applied and iterated on a slice from a dataset, and when the segmentation of a region of interest is completed by opening the next slice and loading this snake, the snake will appear at the same coordinate positions as in the previous slice, and it can then be iterated on the new slice. Hence, no snake initialization is required for the second slice. This results in time saving and simplicity of operation. Fig (7) illustrates this feature of GUI on four successive slices of an MRI dataset. An initial snake is implemented and iterated to segment a desired structure in a slice (i.e., slice 03), and the converged snake is loaded on the successive slice (i.e., 04), for the same structure. Thereafter, by iterating the snake on this slice, it fits itself to the boundary of the structure in this slice and segments the desired structure. This example continues this process on the next slice (i.e., 06).

Fig (7)shows: (a) the initial snake (in red color) on slice 03 of MRI dataset, (b) the final snake (in green color) after 100 iterations when the snake converges to the boundary, (c) the snake (in green color) loaded on the same structure in slice 04, (d) the final snake on slice 04 after 40 iterations, (e) the snake loaded on the same structure in slice 05, and (f) the final snake on slice 05 after 40 iterations. (g) the snake loaded on the same structure in slice 06, and (h) the final snake on slice 06 after 25 iterations. The values of parameters of each slice in the series of a same case may not be similar, for example the no. of iteration in first slice may be 20 and the second slice may be 100.

Note: Medical Images of patients' cases are taken from Hitachi Medical Systems America (4).

Conclusion

It is found that the generic segmentation algorithms (thresholding approaches, region-based approaches, edge-based approaches) are usually easy to use. However, they are all sensitive to noise. They tend to over segment the images. Moreover, the segmentation results may not correspond to the desired object. They failed with the medical images because of the sheer size of data sets and the complexity and variability of the anatomic shapes of interest.

The Snakes Models are the popular approaches currently used in medical image segmentation. The efficiency of snakes depends on a set of parameters such as alpha (elasticity parameter), beta (rigidity parameter), iteration no. etc. When the user gives the appropriate values, the snake deforms well and locks on the desired object. Also it is found that, there is no way to compute or directly give the appropriate values for these parameters, but by experiments and common sense; with respect to our experiments we found that the acceptable range for each parameter is as follows:

Increasing β will increase the rigidity of the model and would affect the shape even if close to start with. We found that the rigidity parameter can be increased from 0 to 0.01 with almost the same results. Decreasing the tension parameter causes the active contour to follow the influence of the external force and lose its smoothness. The acceptable range that we found for tension was from 0.5 to 0.8.

Also it is found that the best combination of the parameters may vary depending on the characteristics of the region of interest (i.e., the contrast and shape), the number of points of the initial contour, and the distance of the points from the boundary.

Finally, it is important to observe that an efficient, precise medical image segmentation system should necessarily add to the model some level of intrinsic knowledge about the problem. Variables like the kind, shape and relative location of the common structures or pathology, and their size compared to some reference system such as an anatomy atlas, would improve enormously the model robustness and autonomy.

Reference

1.Derraz ,F.; Beladgham, M. and Khelif, M., (2004) , IEEE Trans. On Information Technology: Coding and Computing ,8(4):

2.Kass M.; Witkin, A. and Terzopoulos, D., (1986) International Journal of Computer Vision, 1(4) :321-331,

3.Chan T. F. and Vese L. A.,(2001) IEEE Trans. On Image Processing, 10 (2) Feb:

4. Hitachi Medical System America, (2004) Available at: http:// www.hitachimed.com.

Table (1) Kass' snake parameters

Shape	(σ)	(α)	(β)	Iteration No.
Circle	2	0.5	0.05	250
Convex polygon	3	0.7	0	300

Table (2) Kass' snake parameters with medical images

Type of image	(σ)	(α)	(β)	Iteration No.
MRI	3	0.5	0	80
Ultrasound	3	0.8	0.01	260

Do

For each control point (X_i, y_i)

Calculate the local energy of the curve at (X_i, y_i)

Estimate the partial derivatives x_{ss}, x_{ssss}, y_{ss} and y_{ssss} using finite
difference approximations

Calculate the force F_{int} and F_{ext} along x and y directions

Thus calculate the total force experienced by the point (X_i, y_i) in

x and y directions and find the new pixel (x', y') it should move to

Calculate the local energy of the curve at this new pixel (x', y')

Update (X_i, y_i) to (x', y') only if this brings about a decrease in
local curve energy.

END FOR

WHILE number of control points moved > ε

ε is the threshold specified by the user and defines the termination criterion for the loop

Fig. (1) Kass' snake algorithm

(a) (b) (c)

Fig (2) Kass' snake locked on a circle (a) is the initial snake in red color, (b) is the snake deformation in red color, and (c) is the final snake in green color

(a) (b) (c)

Fig (3) Kass' snake locked on a convex polygon (a) is the initial snake in red color, (b) is the snake deformation in red color, and (c) is the final snake in green color

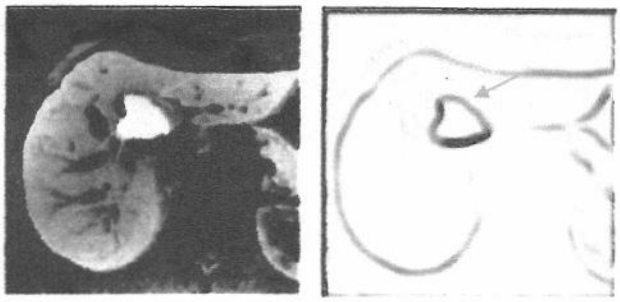
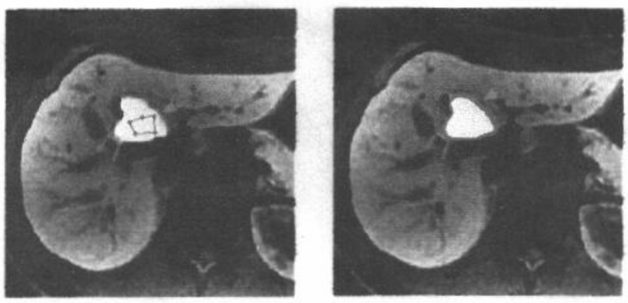
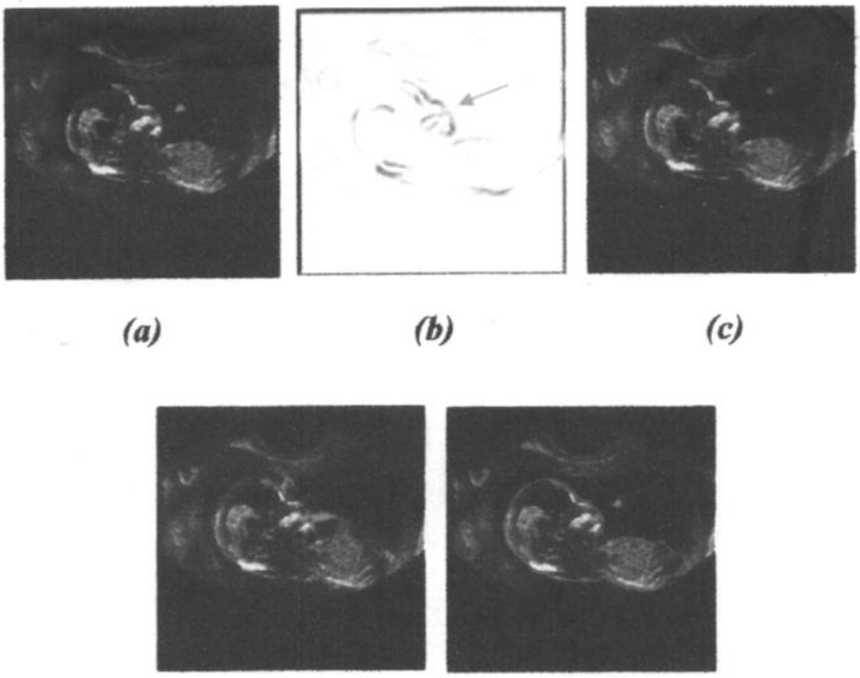


Fig (4) MRI slice liver image corresponding to a patient with a hepatic cystic lesion depicted. Pathological image convolved with a Gaussian filter G_σ ***for*** $\sigma = 2.5$



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

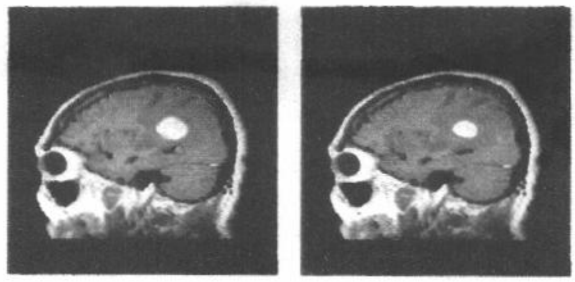
Fig (5) Pathological image segmented with Kass' snake model, (a) is the initial snake red color and (b) is the final snake in green color



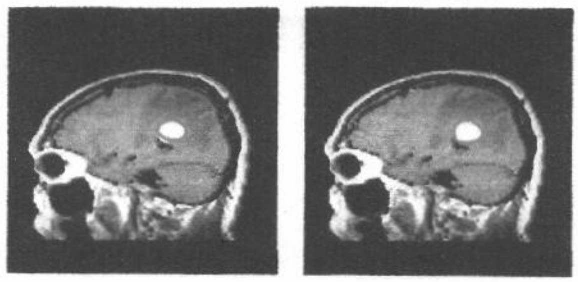
(a) *(b)* *(c)*

(d) *(e)*

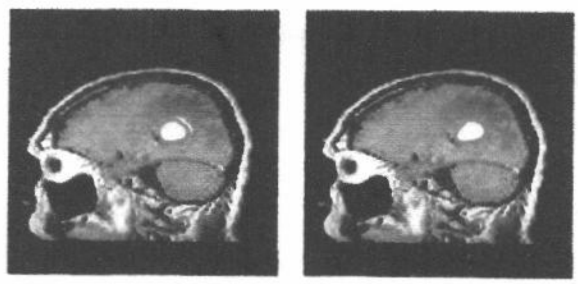
Fig (6) Ultrasound image of embryo segmented with Kass' snake model, (a) is the original image, (b) is the edge map, (c) is the initial snake in red color, (d) is the snake deformation, and (e) is the final snake in green color



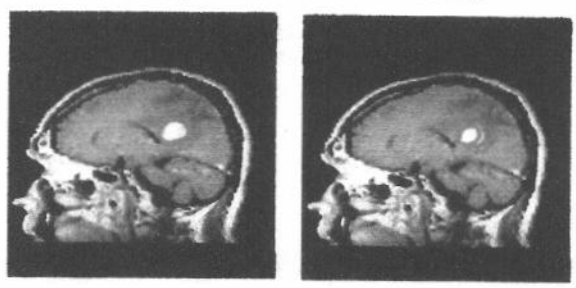
Slice 03 (a) Slice 03 (b)



Slice 04 (c) Slice 04 (d)



Slice 05 (e) Slice 05 (f)



Slice 06 (g) Slice 06 (h)

Fig (7) Example of the multi-loading property of snake in GUI

تطبيق أفعى كاس في تقطيع الصور الطبية

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الخلاصة

الافعى (Snake) هي عبارة عن منحنيات تعمل وفقا لتقليل الطاقة الوظيفية (energy-minimizing spline) وهي تُعّرف في مجال الصورة وتتحرك تحت تأثير قوى داخلية تُشتق من المنحنى نفسه وقوى خارجية تشتق من بيانات الصوره, وهي تعتبر احد نماذج المنحنيات النشيطة (Active contour models) حيث تقوم بالتكور على الحافات وتحديد موقعها بدقة. الافاعي تستخدم في تطبيقات عديدة مثل ايجاد الحافات، الخطوط، و تتبع الحركه. في بحثنا هذا استخدمنا الافاعى بنجاح في عملية التقطيع (segmentation) حيث ان الافعى الابتدائية تُعطى من قبل المستخدم على موقع محدد من الصوره (features of interest) ، تم استخدام افعى كاس في تقطيع الصور الطبية والمتمثلة بصور الرنين المغناطيسي والسونار وتم الحصول على نتائج جيدة حيث تمكنت افعى كاس من تقطيع التراكيب التشريحية في كلا النوعين من الصور بنجاح.