AN INTELLIGENT AND *ATTRACTABLE* ACTIVE CONTOUR MODEL FOR BOUNDARY EXTRACTION

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ABSTRACT

An intelligent and *attractable* active contour model for boundary extraction is presented in this paper. The proposed model is capable of driving any initial guess in the area of the evolving estimate towards the desired boundary, working against a constant image background, overcoming spurious edge-points and fitting into the object without any overrun. It is also capable of extracting both concave and convex boundaries while still being capable of bearing subjective boundaries with help of a synthetic convergent criterion and an adaptable interpolation scheme. Using additional two control parameters, it is possible to control the convergent properties of the new model, which provides a high degree of flexibility and adaptability. This robust model has been applied to real images with encouraging results.

1. INTRODUCTION

In many applications of image analysis, segmenting structures from images is an essential step. The challenge is to extract boundary elements that belong to the same structure and integrate these elements into a coherent and consistent model of structure [1]. Traditional low-level techniques (e.g. thresholding, region growing [2] and edge detecting [3]) which only utilize local information can make mistakes during this integration process and generate erroneous object boundaries. Alternatively, the active contour model, known as snakes [4], offers a unique and effective approach to image segmentation by exploiting (bottom-up) constraints derived from the image data together with (top-down) a priori knowledge about the location, size and shape of these structures. It integrates the image feature extraction and representation phases into a single process. However, the original snake model suffers from the following drawbacks:

- The evolution of a snake highly depends on its initial state (i.e. either position or shape). If the initial contour is not close enough to the object, its energy minimization fails.
- It becomes stagnant at some local minima corresponding to noise in the image due to the inherent tendency to settle into a nearby local energy minimum [5].
- It lacks the ability to handle concave or convex contours properly [6].
- The single convergent criterion leads to the snake fail under certain adverse condition [6][7]

In this paper, a new model, an *attractable* snake, is proposed to overcome the above limitations of snake. Unlike other improved models, such as the region based model [2], balloon model [5] and dual snake model [8], which only depend on the specific geometrical properties of the snake and lack robust automatic optimization mechanism, our intelligent *attractable* contour model is built to directly sense its potential energy variation (i.e. voltage) of image attributes (e.g. edges) to perform minimization process automatically from a given initial guess without restrictive constraints (i.e. position and shape). it can converge to the desired minima at original snake's equilibrium without any overrun.

2. THE CONVENTIONAL SNAKE MODEL

In general, a deformable contour, snake, is a parametric contour embedded in the image plane $(x, y) \in \Re^2$. The contour V(s) having arc length s as a parameter can be represented as below:

$V: \Omega = [0, 1] \rightarrow \Re^2$

$$V(s) = [x(s), y(s)] \quad \text{where } s \in \Omega \tag{1}$$

Let A_d be a space of admissible deformations. The shape of the contour subject to an image I(x, y) can be dictated by its energy function E_{snake} as follows:

$E_{snake} : A_d \rightarrow \Re$

$$E_{snake}[V(s)] = \int_\Omega \{ E_{int}[V(s)] + P_{image}[V(s)] + E_{const}[V(s)]\} ds \tag{2}$$

where $E_{int}[V(s)]$ represents the internal energy term which imposes the regularity on the curve by bending and stretching, given by

$$E_{\text{int}}[V(s)] = \frac{1}{2}\{\alpha(s)|\frac{\partial[\text{v}(s)]}{\partial s}|^2 + \beta(s)|\frac{\partial^2[v(s)]}{\partial s^2}|^2\} \tag{3}$$

where the primes α(s) and β(s) control the mechanical properties (i.e. elasticity and rigidity) of the model. $P_{image}[V(s)]$ represents the image potential energy term that attracts the snake toward salient image attributes, such as lines, edges and subjective contours. For edges, it is defined as follows:

$$P_{image}[V(s)] = -\gamma(s)|\nabla I[V(s)]|^2 \tag{4}$$

where the prime γ(s) controls the weight of image attraction and ∇I[V(s)] represent the image gradient. $E_{const}[V(s)]$ represents the external constraint energy term that is responsible for guiding the snake towards the desired local minimum. It can be defined by the user, constructed from physical phenomena [7], or derived from high-level interpretation [4].

The final shape of the contour corresponds to the minimum of this energy:

$$E^{*}_{snake} = \min \{E_{snake}[V(s)]\} \quad (5)$$

The above equation was originally solved by use of techniques of variational calculus and a Finite Difference Method (FDM) is applied [4]. Later, it was improved by Cohen [5] using a Finite Element Method (FEM).

Another solution is found by Amini using dynamic programming [9] that promotes stability of snakes and hard constraints to be enclosed at cost of expensive computation. Nevertheless, Williams [10] improves this by taking the bold step of searching in a greedy fashion to found solution for the above energy minimizing functional (5). Besides, Lam et al [11] proposed an alternate searching pattern based on connective characters of four and four diagonal neighbors of an image point to reduce the computing time by 30% average.

In this paper we will work on the base of both the greedy algorithm and the fast greedy algorithm to control snakes because they reasonably combined speed, flexibility and simplicity compared to the dynamic programming and the variational calculus based methods

3. *ATTRACTABLE* SNAKE MODEL

Our *attractable* snake model id defined as follows:

$$E_{snake}[V(s)] = \int_{\Omega}\{E_{int}[V(s)] + P_{image}[V(s)] + E_{feedback}[V(s)]\}ds \quad (6)$$

where $E_{int}[V(s)]$ and $P_{image}[V(s)]$ are as given in equations (2) and (3) respectively. $E_{feedback}[V(s)]$ is defined by the following equation:

$$E_{feedback}[V(s)] = - f_{db}(s)\nabla P_{voltage}[V(s)]\mathbf{n}(s) \quad (14)$$

where **n**(s) is a unit vector which represents the direction of normal to deformable contour in A_d. $E_{feedback}[V(s)]$ is designed to directly reflect the potential energy variation $\nabla P_{voltage}[V(s)]$ of image features (i.e. edges). In fact $P_{image}[V(s)]$ of the snake model serves as a potential field which can attract a snake to salient image features. We call this field the image feature potential energy field, which is similar to a magnetic field. If the attraction from the desired image feature is large enough to overcome the internal mechanical resistance (due to bending and stretching) of the contour, and with the condition that there is no external energy influencing, the snake can then be attracted to the attraction source and adhere to it. Obviously the deformation movement of snake depends on the distance between the deformable contour and the desired image feature. However, we do not always know exactly how far from the initial contour this attraction source is, but it can only adhere to the attraction source when it is close enough to the object contour. Concurrently, we can determine what kind of potential energy the desired feature should posses from the edge information and what kind of potential energy the deformable contour has in this field after being given the initial contour guess (i.e. the potential energy of every point on the deformable contour and its neighbors). Based on these information we are able to construct the above feedback mechanism about the attraction energy variation to drive the snake deformation (i.e. expansion or contraction) along its normal direction, until it fails into the desired image feature.

3.1 Implementation

The following equation is our *attractable* snake model for a discrete curve:

$$E_{snake}[V(s)] = \sum_i [E_{int}(V_i) + P_{image}(V_i) + E_{feedback}(V_i)] \quad (8)$$

where $E_{int}(V_i)$, $P_{image}(V_i)$ and $E_{feedback}(V_i)$ are given by equation (9), (10) and (11) respectively.

$$E_{int}(V_i) = \alpha(i)E_{cont}(V_i) + \beta(i)E_{curv}(V_i) \quad (9)$$

where,

$$E_{curv}(V_i) = \frac{|V_{i-1} - 2V_i + V_{i+1}|^2}{\max_j \{|V_{i-1} - 2V_i + V_{i+1}|^2\}}$$

$$E_{cont}(V_i) = \frac{d - |V_i - V_{i-1}|}{\max_j \{d - |V_{i,j} - V_{i-1}|\}}$$

where d is the average curve length and $V_{i,j}$ are the 8-neighbors of a point V_i on the curve (i=0, 1, 2,…, n) for j=0, 1, 2, …, 8.

$$P_{image}(V_i) = \gamma(i)P_{field\text{-}norm}(V_i) \quad (10)$$

where,

$$P_{field-norm}(V_i) = \frac{P_{field-\min} - P_{field}(V_i)}{P_{field-\max} - P_{field-\min}}$$

where $P_{field}=|\nabla I(V_i)|$ according to the Greedy algorithm [13]. $P_{field-max}$ and $P_{field-min}$ are respectively the maximum and minimum values of P_{field} in 8-neighborhood of V_i.

$$E_{feedback}(V_i) = -f_{db}(i)\nabla P_{voltage}(V_i)\mathbf{n}(i) \quad (11)$$

where,

$$\nabla P_{voltage}(V_i) = \begin{cases} \dfrac{P_{\max} - \frac{1}{8}\sum_{j=1}^{8} P(V_{i,j})}{P_{\max}} & \text{if } P(V_{i,0}) < P_{level} \\ 0 & \text{if } P(V_{i,0}) \geq P_{level} \end{cases}$$

where P_{max} and P_{level} are respectively the maximum and threshold level in the potential field of image features.

$E_{feedback}(V_i)$ is designed to respond to the variation of potential energy of the snake while it is driven close to the desired contour and will disappear automatically when the snake reaches the object. Hence, the improved model can achieve the equilibrium of the original snake. In another words, the new model can reach the desired local minima without any overrun. Meanwhile, $E_{feedback}(V_i)$ is also designed to respond to the variation of potential energy of eight neighbors of the snake points while it is driven close to the desired contour points. Therefore, our intelligent model can control the speed of a snake approaching the desired contour and ensure snake to sense the local shape of potential field properly (i.e. the snake to be trapped by the desired contour without overrun), as shown in Fig. 1.

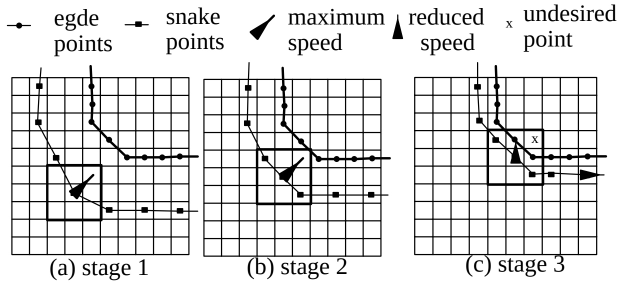

Figure 1. Movement of the snakes with $E_{feedback}$.

Here α(i), β(i) and γ(i) are the same as in original model whereas $f_{db}(i)$ is for feedback pulling (for expansion) or pushing (for contraction) on snakes and is simply chosen smaller than γ(i) and slightly larger than α(i) or β(i), or both. By changing the direction of the **n**(i), we can control an effect of shrinking instead of expanding, or vice versa.

The idea of our new model is similar to Cohen's balloon model [5]. However, in that model, the normal force was not derived from object feature potential and only depends on the position of V(s). Furthermore, when the balloon reaches an equilibrium, the points of the snake are slightly outside the real contour since the image force has to be in equilibrium with the inflation and regularization forces.

3.2 Construction of Potential Field (Edge Image)

An overall optimal edge detection scheme is employed in order to promote our snake perform successfully with low contrast and noisy images. As shown on Fig. 2, we first split a 2-D Gaussian smoothing filter into two directions (i.e. x and y), then implement a smoothing operator with the opposite sequence of Sobel edge detecting. In fact, this approach presents stronger edge strength, more competitive noise suppression, higher efficiency in weaker edge detection and lower time cost compared to the Canny detector [3]. We use a 1-D Gaussian filter to enhance the inherent smoothing result of the Sobel operator in the same direction rather than a 2-D filter, in order to improve the result of the Sobel operator, avoid blurring edges and reduce the computational cost.

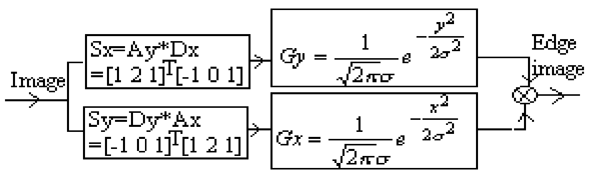

Figure 2. The overall optimal edge detection

3.3 Synthetic Convergence Criterion

The original convergence criterion of the greedy algorithm [11] or the fast greedy algorithm [12] totally depends on the movement of snake points but does not ensure snakes reach their equilibrium [5][11][12]. Since we calculate at a discrete point of the image. Therefore, it has an inherent numerical instability (i.e. it oscillates about the equilibrium), if the equilibrium of snake falls into a non-integer location. In order to avoid such instability, we propose a suitable synthetic convergence criterion based on the following characteristic parameters of snakes approaching equilibrium:

- After achieving equilibrium, the snake tends to be static.
- The length of contour tends to be a constant.
- Image energy of curve tends to be a constant value.

Fig. 3 illustrate the proposed synthetic convergence criterion. Unlike other single criterion, such Cohen's curve displacement [5], Leymarie's image energy change [7], or Yung's CL-Criterion [6], our convergence criterion allows snakes to either oscillatingly or normally converge to either a usual contour or a subjective contour.

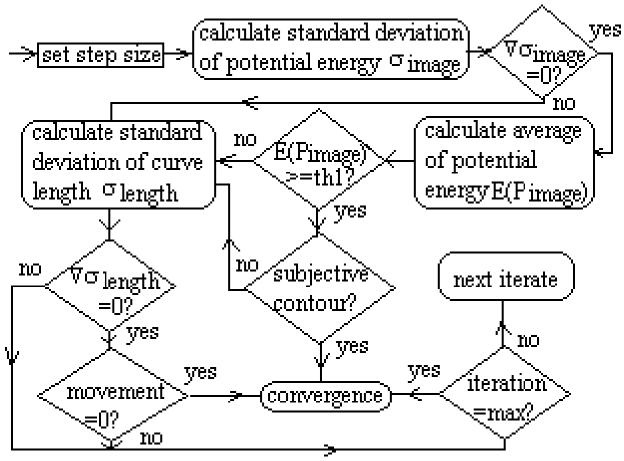

Figure 3. The improved convergent criterion

3.4 Adaptable Interpolation Scheme

In addition, a method of dynamic, linear interpolation is employed to promote snakes to sense the local shape of the desired contour accurately or to flow into the complicated shape (i.e. concave or convex contour) of the object contour properly. To avoid re-parametering after each interpolation and to maintain the continuity of optimizing iteration, we retain the original parameter setting at each contour point and give the neighboring point's setting to each new contour point. GAP is the threshold for average length of the contours and can reflect the basic geometric property of snake. Therefore in order to avoid clustering or even looping we remove those snake points becoming much closer to its previous point according to GAP (i.e. when GAP=0, 1, 2) during each interpolation.

4. RESULTS AND CONCLUSION

In order to demonstrate the performance of our proposed model, results are give in Fig. 4 for the model based on both the greedy algorithm (top right of (a)-(d)) and the fast greedy algorithm (bottom right of (a)-(d)) as well. The images for (a) and (b) are obtained by digital camera by resolution of 11.29cmx8.47cm, 56.963 pixel/inch. The image for (c) is an axial spin echo MRI image of the chest taken during clinical examination using the cardiac gating technique. The slice for (d) is the axial anatomical spin echo MRI image of heart with interval of 1mm and 0.33mmx0.33mm pixel size. All initial contours are placed manually and superposed in both original images (top left of (a)-(d)) and edge images (bottom left of (a)-(d)). All parameters were set experimentally and shown in Fig. 4.

Our experiments show the four important aspects of our new model: Firstly, it keeps its traditional properties associated with original model while it overcomes the limitations of the original model of being sensitive initial condition and spurious edge point. Secondly, it reaches the desired object without any overrun. Thirdly it can catch the details of object contour most correctly. Finally it makes snakes dealing with concave or convex contours. By building a feedback mechanism we achieve an automatic optimising process. With the help of a new synthetic convergence criterion the snake can converge both normally and oscillatingly to the desired contour. With an adaptable, dynamic linear interpolation scheme we obtain simple control of topologic property of snake. However, a suitable topologic deformation scheme can be used to extend this model to multi-snakes [1][6].

5. REFERENCES

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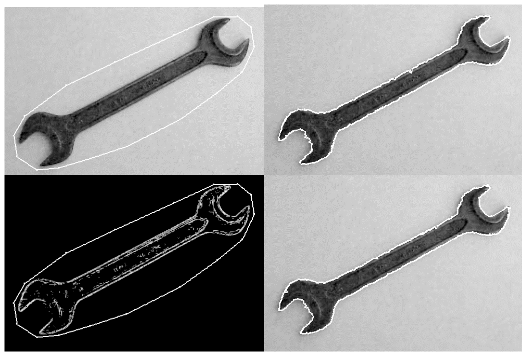
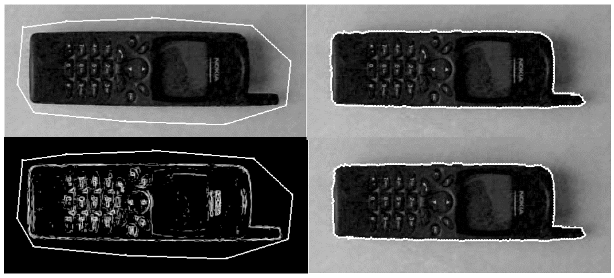
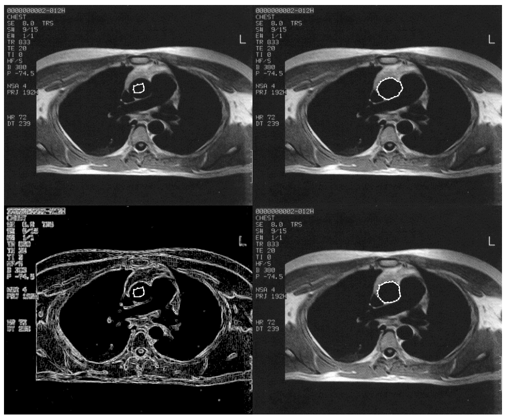


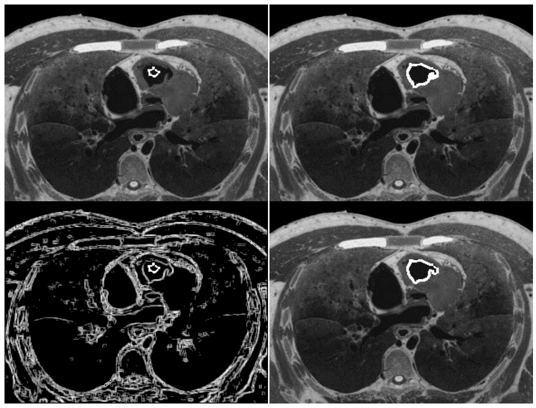
(a) α=0.79/0.78, β=0.68/0.67, γ=0.9, f_{db}=0.6, GAP=5;



(b) α=0.47/0.48, β=0.9, γ=0.9, f_{db}=0.415/0.42, GAP=4;



(c) α=0.94, β=0.93, γ=1.2, f_{db}=0.915, GAP=9;



(d) α=0.85/0.73, β=0.81/0.4, γ=1.3, f_{db}=1.3/1.05, GAP=4;

Figure 4. Experiment results of our new snake model