Images Boundary Extraction Based on Curve Evolution and Ant Colony Algorithm

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Abstract. A new boundary contour extraction algorithm based on curve evolution model and ant colony algorithm is proposed in this paper. Firstly, ant colony algorithm is used to find the optima of snake points for rapidly converging near image edge. Then the interpolation algorithm is applied to gaining the object's rough contour that is used as the initial zero level set. The accurate contour can be obtained by the curve evolution method. Experimental results are given to demonstrate the feasibility of the proposed method in extracting contour from the blurred edge and high-noise images.

Keywords: Boundary extraction, Ant colony algorithm, Curve evolution, Mean-shift.

1 Introduction

Curve evolution is more accurate image processing method, widely used in medical image processing, computer vision and other fields. A great deal of research is made on curve evolution model and it's numerical, a number of representative methods are proposed. For example, Kass and Witkin, based least energy, give a parameters curve method (snake) [1]; Caselles proposed deformation geometry (geometric active contour) and geodesic (Geodesic Active Contours) curve evolution model [2] [3]; Osher and Sethian raised the level of set theory [4]. Mumford-Shah variation model [5] (referred to as the model for MS) is from 1989 proposed by Mumford and Shah, and the model has adaptive capacity for evolution curve topology analysis. The model, adopting the variations method, turns the problem of image contour extraction into a functional extreme value problem. Its energy function included in the border region and outline description of the image. As the MS is a model of modern mathematics in a freedom and not continuous issues, the function easily fall into the local minimum, which difficult to get numerical value in practical applications. CV model is a simplified model of MS give by Chan and Vese [6], based on the method in literature [5]. The energy evolution function does not rely on images gradient, but on the region. This method is suitable for gradient meaningful or meaningless contour extraction, also for the fuzzy or not continuous edge. The literature [6] define the energy function based on the level set, solving the evolution of partial differential equations (PDE) by Euler method, and get the image contour by repeated iterative. In order to meet the

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stability and convergence requirements, whether adopt explicit or implicit iterative method, the step size must be small enough. After each updated, it need to re-initialize the function (SDF) in order to maintain the stability of the calculation. Because of large calculation and the slower evolution speed, there are many restrictions in their actual application. Literature [7] improves the partial differential equations' solve of Euler-Lagrange, and constructs a rapid SDF structure.

In literature [8], a curve and layered evolution model and multi-level set equations are given. Jingfeng Han [9] gives a border matching algorithm combining contour extraction and registration. Using MS model and its automatic coupling function to express border characteristics, curve evolution is divided into two parts, linear and nonlinear, and by computer by the finite element method and the gradient descent iterative respectively. Using high-frequency filter component as the coupling function of curves evolution, Xaiojun Du improved the MS model [10], and speed up the solution of evolution function by single-variable PDE and high-frequency deconvolution filtering.

Ant algorithms have generated significant research interest within the search/ optimisation community in recent years. Ant algorithm has been successfully used to solve many NT' problems, such as TSP, assignment problem, job-shop scheduling and graph coloring. The algorithm has inherent parallelism, and we can validate its scalability. A colony of ants begins with no solutions. Each ant constructs a solution by making decisions stochastically, using existing problem constraints and heuristics combined with experience (which is analogous to a substance called pheromone). The colony then reinforces decisions in the construction process according to their successes by adding pheromone, which also decays to mitigate against poorer decisions[11][12].

In this paper, MR images' boundary is extracted by ant colony algorithm and curve evolution method. It can lower the jitter of evolution curve caused by fuzzy edge and uneven gray.

2 Ant Colony Algorithm

Ant algorithm is a method to solve combinatorial optimization problems by using principles of communicative behavior occurring in ant colonies. Ants can communicate information about the paths they found to food sources by marking these paths with pheromone. The pheromone trails can lead other ants to the food sources. Ant algorithm is an evolutionary approach where several generations of artificial ants search for good solutions. Every ant of a generation builds up a solution step by step thereby going through several decisions until a solution is found. Ants that found a good solution mark their paths through the decision space by putting some amount of pheromone on the edges of the path. The following ants are attracted by the pheromone so that they will search in the solution space near good solutions.

Let m be the number of ants; η_{ij} be the visibility of edge (i, j); τ_{ij} be trail degree of edge (i, j); $\Delta\tau_{ij}^{k}$ be pheromone of per length on edge (i, j) leaved by ant k ; P_{ij}^{k} be transition probability of ant k ; α be relative importance of trail

($\alpha \geq 0$); β be relative importance of visibility($\beta \geq 0$); ρ be the permanence of trail($0 \leq \rho < 1$), and $1-\rho$ be the attenuation degree of trail.

State transition rule the probability of selecting j as next point to visit, taking stochastic proportion, when ant k at point i. The probability can be calculated by the formula as follows.

$$P_{ij}^{k} = \begin{cases} 1, & q < q_0, j = \max_{r \in A_i} \{\tau_{ir}{}^{\alpha} \eta_{ir}^{\beta}\} \\ 0, & q < q_0, j \neq \max_{r \in A_i} \{\tau_{ir}{}^{\alpha} \eta_{ir}^{\beta}\} \\ \dfrac{\tau_{ij}{}^{\alpha} \eta_{ij}^{\beta}}{\sum_{r \in A_k} \tau_{ir}{}^{\alpha} \eta_{ir}^{\beta}}, & q \geq q_0 \end{cases} \tag{1}$$

where q is a random number($0 < q < 1$), and q_0 is a given valve value, A_k is the reachable point set of ant k at point i.

Trail updating may be done after each successive move of the ant (termed local updating) or after all ants have completed one cycle (global updating). In local updating, pheromone values are updated on edge (i, j) every time an ant moves from point i to point j. The new quantity of pheromone deposited on an edge is inversely proportional to the edge length; thus, over time, shorter edges will receive more pheromone, which leads to a positive feedback loop of increased use and further reinforcement. During global updating, only one ant is allowed to update the trail values. This elitist strategy requires that only the ant with the iteration-best tour be allowed to deposit additional pheromone. Similar to local updating, the new quantity of pheromone deposited is inversely proportional to a certain value; this time, the value in question is tour length, not edge length. Thus, edges which constitute shorter tours are reinforced more which leads to another positive feedback loop of more use and greater reinforcement. Trail updating rule can be expressed as follows.

$$\tau_{ij} = (1-\alpha)\tau_{ij} + \alpha\Delta\tau_{ij} \tag{2}$$

3 Curve Evolution

In [6] T.F Chan and L.A. Vese proposed an active contour model using an energy minimization technique. Assume that the image u_0 is formed by two regions of approximately piecewise constant intensities u_0^i and u_0^o, and the object to be detected is represented by the region with value u_0^i. If the boundary is given by c_0 ,then $u_0 \approx u_0^i$ inside c_0 and $u_0 \approx u_0^o$ outside c_0.

The energy F defined by:

$$F = F_1(C) + F_2(C) = \int_{inside(C)} \left|u_0 - c_1\right|^2 dx + \int_{outside(C)} \left|u_0 - c_2\right|^2 dx \tag{3}$$

where c is any variable curve, c_1 and c_2 are constants depending on c .Therefore, The energy F is minimized when $c = c_0$:

$$F = \inf\{F_1(C) + F_2(C)\} \approx F_1(C_0) + F_2(C_0) \approx 0 \tag{4}$$

C is represented by the zero level set of the function $\phi : R^N \rightarrow R$:

$$\begin{cases} C = \{x \in R^N : \phi(x) = 0\} \\ C_{inside} = \{x \in R^N : \phi(x) > 0\} \\ C_{outside} = \{x \in R^N : \phi(x) < 0\} \end{cases} \tag{5}$$

Using the standard definition for the Heaviside function H .

$$H(z) = \begin{cases} 1 \text{ if } z \geq 0 \\ 0 \text{ if } z < 0 \end{cases} \tag{6}$$

Area inside C= $\int_\Omega H(\phi)dx$, thus

$$F(\phi, c_1, c_2) = \int_\Omega \left|u_0 - c_1\right|^2 H(\phi)dx + \int_\Omega \left|u_0 - c_1\right|^2 \{1 - H(\phi)\}dx \tag{7}$$

Minimizing the energy function with respect to C_1 and C_2 gives

$$C_1(\phi) = \frac{\int_\Omega u_0 H(\phi)dx}{\int_\Omega H(\phi)dx} \tag{8}$$

$$C_2(\phi) = \frac{\int_\Omega u_0\{1 - H(\phi)\}dx}{\int_\Omega \{1 - H(\phi)\}dx} \tag{9}$$

In the classical explicit snake model [1] the parametric curve is embedded into an energy minimization framework. However, the parametrization of the curve causes difficulties with respect to topological changes and numerical implementations. Thus, to prevent these difficulties, implicit active contour models have been developed. The basic ides is to represent the initial curve implicitly within a higher dimensional function, and to evolve this function under a partial differential equation.

Our model is the minimization of an energy based on segmentation. In our implicit scheme the energy minimization parameter is embedded into the diffusion equation. The evolving contour model is given by the following evolution equation:

$$\frac{\partial u}{\partial t} = g(\left|\nabla G_\sigma * u\right|^2)\left|\nabla u\right| div\left(\frac{\nabla u}{\left|\nabla u\right|}\right) + \alpha\left|\nabla u\right|F \tag{10}$$

In order to reduce smoothing at edges, the diffusivity g is chosen as a decreasing function of the edge detector $|\nabla G_\sigma * u|$. Here, $\nabla G_\sigma * u$ is the gradient of a smoothed version of u which is obtained by convolving u with a Gaussian of standard deviation σ.

4 Boundary Extraction Model

During boundary extraction, the traditional curve evolution model is easy to make a curve points converge on individual noise points, so noise has a significant influence to evolution model. In this paper, Ant colony algorithm based active contour model is used to quick search and optimize the control points, and it can make quickly converge to the edge of the image. And then using interpolation algorithm, we get the rather rough outline of goals. In next step, taking the outline as the initial object contour of zero level set curve.

The mean-shift algorithm is a nonparametric statistical method for seeking the nearest mode of a point sample distribution. Mean shift is a simple iterative procedure that shifts each data point to the average of data points in its neighborhood. Given a set of data point x_i, the mean shift vector in a simple one-dimensional case can be expressed as[13]:

$$m(x) = \frac{\sum_{i=1}^{n} x_i g((x - x_i / h)^2)}{\sum_{i=1}^{n} g((x - x_i)^2)} - x \tag{11}$$

where x is an arbitrary point in the data space (it can even be one of the x_i points), h is a positive value called the analysis bandwidth and $g(u)$ is a special function with bounded support; $g(u)$ is defined as the first derivative of another bounded-support function.

When $m(x)$ is applied to the original point, x, it results in anew position, x^1; this process can be repeated and an iterative procedure defined in this way:

$$x^{l+1} = m(x^l) + x^l \tag{12}$$

Here is the process of boundary extraction method by ant colony algorithm based active contour model:

(1) Given the initial position of ant swarm, $x_1, x_2, ..., x_i$;

(2) Set every parameter of ant algorithms;

(3) In general, guide function is taken as $\eta = 1 / d_{ij}$. In our method, η is defined as: $\eta = \frac{r}{d_{ij} + | \sum_{i=1}^{k} h_i / k - \sum_{j=1}^{k} h_j / k |}$. r is clustering radius;

(4) P_{ij}^k According to equation (1), calculation the probability P_{ij}^k that integrated x_j into x_i. If $P_{ij}^k \geq q_0$, x_j class will be integrated into x_i class;

(5) Adjust the amount of permanence on the path;

(6) Recalculate the initial position x_i'. $x_i' = \frac{1}{N}\sum_{k=1}^{N} x_k$ $x_k \in class$ of x_i;

(7) When iterative finished, the algorithm is end, and the points of initial zero level set curve is x_i';

(8) Using interpolation algorithm to get the object's rough contour;

(9) Using curve evolution method to get the accurate contour.

5 Experiments

All algorithms were coded in Microsoft Visual C++ version 6.0 and all experiments were run on a PC Pentium IV 1.8GHz with 256MB RAM running under Microsoft

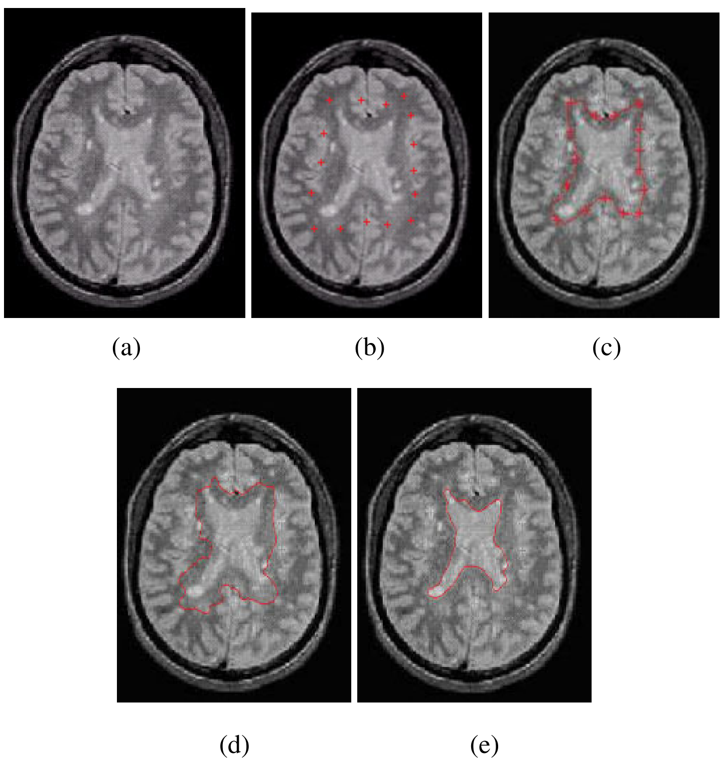

Fig. 1. (a) Original image (b) initial position (c) initial evolution curve (d) traditional curve evolution method (e) Ours

Windows 2000. The parameters of ant colony algorithm are: $\alpha = 3, \beta = 1, \rho = 0.3$. In order to validate the actual results, in this paper, we select brain MR image. MR images are well classified into grey matter, white matter, cerebrospinal fluid, scalpbone, and background. Here, we present numerical results using our model. Figure 1(a) is the original image. Figure 1(b) is the initial position of ant swarm. Figure 1(c) is the initial evolution curve. Figure 1(d) is extraction result by traditional curve evolution method; with the initial curve that interpolation by figure 1(b), which takes 50th iteration. Figure 1(e) is used ours method, which takes 50th iteration. According to the results, our proposed model can be effectively extracted the border of brain tissue, outlining the objectives boundary for the fuzzy part and the gradual change.

6 Conclusion

According to the curve evolution theory and ant colony algorithm, a new boundary contour extraction algorithm is proposed. There are many problem in MR images, such as the border region fuzzy, gray uneven, difficult positing the border. Using ant colony algorithm, the initial evolution is get, and then the boundary is extraction by curve evolution. The approach automatically detect smooth boundaries, and change of topology. Experiments show that ours method can effectively lays out the fuzzy image and discontinuous marginal.

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