An Improved Active Contour Model in Medical Image Segmentation

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Abstract. Aiming at the problem that medical image segmentation has low precision because of restriction of image principle, this paper proposes an improved active contour model based on vector field convolution, and combining both the balloon force and gradient directional information. This method improves the energy function of model, has more chances to approximate the complex boundary. The experimental results show that the new model not only inherits the advantages of the previous models, but also show fast speed, limits the influence of false edge and noise disturbance.

1. Introduction
Active contour model is a curve or a surface defined within the image range that can be deformed by the interaction of the internal force of the curve or the surface itself and the external force generated by the image data. The ultimate goal of deformation is to make the curve or plane coincide with the edge of the target object or the shape of the feature that is desired to be detected in the image. More intuitive, we can think of the boundaries of an image as a landmark map, and a variable curve can travel through it. If a force is applied to the curve, the curve moves toward the landmark to achieve energy balance. The forces guiding the motion of a curve can be divided into two categories: one is to guide how the curve moves (either to maintain the original shape or to become another shape), and the other is to guide the curve to move in the target direction. We want the curve to find the outline of the target object, and the outline can be thought of as a negative boundary map, so a balance equation can be established to minimize the overall energy.

The first active contour model was proposed by Kass [1] in 1987. Since the traditional active contour model has some insurmountable shortcomings, the researchers have proposed some improved methods. The Helmholtz theory states that a static vector field can be divided into two components: an irrotational component and a solenoidal component. Since the initially obtained potential capacity field is a scale potential function of the gradient, it can be transformed into an irrotational field called the Gradient Vector Flow (GVF) [2] field. By solving a vector diffusion equation obtained from the boundary map of the image, a vector density field-gradient vector flow field can be obtained. Li and Acton [3] introduced a kind of new model called VFC model based on vector field convolution. This new model not only has a large convergence range and the ability to converge to the concave region, but also has a small amount of calculation cost and can effectively overcome the noise interference.

These existing active contour models reduce the sensitivity to weak noise, parameters and initial positions, but high curvature, strong noise and weak contrast boundaries still bring difficulties to them. In response to these limitations, this paper proposes a new method to improve the segmentation accuracy. The method consists mainly of two parts: First, the balloon force is added to the external
force to accelerate the evolution. Second, we have improved the VFC model by including gradient direction information in the external image force. This additional information help prevent the active contour from crossing weak boundaries, increase speed of model convergence and obtain better segmentation results.

2. Active Contour Model

The traditional active contour model is curves defined in the image plane. It moves in the image space to minimize the energy function below:

\[
E = \int_0^1 \left[ \frac{1}{2} \left[ \alpha |X'(s)|^2 + \beta |X''(s)|^2 \right] + E_{ext}(X(s)) \right] ds
\]

The optimal solution is achieved when the energy minimization process reaches equilibrium, i.e., the energy function reaches a local minimum. Note that this method does not guarantee a global minimum, which is why user interaction is required.

where \( x'(s) \) is the first order derivative of \( x(s) \), \( x''(s) \) is the second order derivative of \( x(s) \) and \( \alpha \), \( \beta \) respectively control tension and rigidity of weights. \( E_{ext}(X(s)) \) is the external energy, for a given image, an external energy term can usually be defined as:

\[
E_{ext} = -\|\nabla I(x, y)\|^2
\]

or

\[
E_{ext} = -\|G_\sigma(x, y) \ast I(x, y)\|^2
\]

where \( G_\sigma(x, y) \) is a Gaussian with standard deviation \( \sigma \) and \( \nabla \) is a gradient operator. In order to minimize the energy function, the snake model needs to satisfy the Euler equation:

\[
\alpha X''(s) - \beta X'''(s) - \nabla E_{ext} = 0
\]

The Eq. (4) is a force balance equation:

\[
F_{int} + F_{ext} = 0
\]

The internal force \( F_{int} = \alpha X''(s) - \beta X'''(s) \) prevents curve from stretching and bending, and the external forces \( F_{ext} = -\nabla E_{ext} \) drives the curve to move toward the desired edge of the image. To solve the equation Eq. (4) dynamically, you can think of \( X \) as a function of time \( t \) and arc length \( s \). Then the partial differential equation of \( X \) for \( t \) is equal to the left end of Eq. (4)

\[
X_t(s, t) = \alpha X''(s) - \beta X'''(s) - \nabla E_{ext}
\]

When \( X(s, t) \) tends to be stationary and \( X_t(s, t) \) tends to zero, the solution of the equation (4) can be obtained.

One of the problems of traditional active contour model is that the initial contour should be close to or located inside the image. If it is not close enough, the snake model will balance itself according to its internal force, and may even collapse on its own. In order to overcome this problem, Cohen [4] proposed to increase the external force term "balloon power". It represents external forces in the normal direction, causing snakes to expand or contract. In the process of optimization, the internal force and image force will gradually restrain the expansion force, but the latter can help the snake model to ignore the insignificant image features in its evolutionary process. The Eq. (7) denotes balloon force, where \( n(s) \) is the normal unit vector of the curve at the point. The sign of \( K \) distinguishes contraction from expansion.

\[
f_{bal} = kn(s)
\]

The balloon force can enlarge or reduce the contour, which is considered to increase the capture range of image power. The balloon force also allows the contour to cross false local image boundaries.
or noise, reduce the sensitivity of the initialization position of contour and image noise, and make it ideal for finding smooth and consistent targets.

The vector field convolution (VFC) model is proposed as a new kind of deformable model which is obtained by convoluting the boundary mapping of the image with a vector field core similar to gravity:

\[ f_{\text{VFC}}(x, y) = f(x, y) * K(x, y) \]

where \( f(x, y) \) is the edge map of the original image and \( K(x, y) \) is the vector field kernel and it can be computed as:

\[ K(x, y) = m(x, y)n(x, y) \]

where \( m(x, y) \) is the magnitude of the vector at point \((x, y)\) , \( n(x, y) \) is the unit vector pointing to the kernel origin point \((0, 0)\) , \( m \) and \( n \) are defined as:

\[ n(x, y) = [-x/r, -y/r] \]

\[ m(x, y) = (y + \varepsilon)^{-\gamma} \]

where the radius \( r = \sqrt{x^2 + y^2} \) is the distance from the origin and it can control the decrease and to prevent division by zero at the origin, \( \varepsilon \) is a small positive constant.

3. The Proposed Model

The VFC model reduces the impact of noise interference, and has a stronger capture capability. However, in some special cases, such as simple circular contour extraction, the balloon model shows faster speed because the computational cost of the VFC model is increased when the image is convolved with the vector field core. According to [5], the GVF snake can be combined with the balloon force to improve the convergence speed. This can also be applied in VFC model. Then the new external energy function is defined as:

\[ F_{\text{ext}} = r_1f_{\text{bal}} + r_2f_{\text{VFC}}(x, y) \]

where the two \( r \) parameters represent the weights of the two external forces respectively. The first force is static and tries to move each point of the model along its normal, just like a classic balloon snake. This balloon force is applied in a dynamic manner: in the early stages of evolution, the balloon force is greater than the VFC force, and the balloon force is given a lower weight at a later stage. In this way, the convergence speed increases, and even if the initialization curve is far from the target, the curve can be correctly pushed toward the target contour.

The weight of the balloon force becomes smaller when approaching the actual edge of the image, and the second force \( f_{\text{VFC}} \) based on the vector field convolution model is used to refine the convergence [6, 7] in order to better capture small morphological changes and thus accurately determine the edge of the target image. Based on the fact that the active contour is mainly driven by the balloon force near the edge, the diffusion radius of the VFC core remains small set to 20 pixels.

In the active contour model, the external force is to attract the contour to the edge of the target image, but both the traditional snake model or the VFC snake model define their external force as a function of the image gradient without considering the direction information of the image gradient. Therefore, the contour sometimes cannot distinguish between the correct weak edge and the false strong edge [8]. In order to make reasonable use of the gradient direction information, the external force of the image can be changed as

\[ f_{\text{VFC}}(x, y) = \begin{cases} f_{\text{VFC}}(x, y) & \text{if } \theta < \theta_1 \\ (-\alpha X'(s) + fX'(s) - r_1 f_{\text{bal}})/\gamma_2 \text{ else} \end{cases} \]

where the \( f_{\text{VFC}} \) is the new force field, \( X_1 \) is one of the points on the contour and \( X_2 \) is the next evolution position of \( X_1 \), then the directions of the VFC vectors at points \( X_1 \) and \( X_2 \) are \( \theta_1 \) and \( \theta_2 \). Set \( \theta = [\theta_1, \theta_2] \), \( \theta_1 \) is a suitable threshold. If \( \theta \) exceeds \( \theta_1 \), which usually means that the contour of the evolution reaches the actual boundary of the object, the evolution should be stopped. This improved force field
introduces a new kind of evolutionary stop mechanism, when the contour reaches the actual edge of the object image, the new VFC force field will stop the continuous evolution of the contour to obtain more accurate results. This important modification avoids contours crossing real target edges due to noise or more attractive false edges.

4. Experimental Results

The performance of our proposed model is compared to the traditional GVF model and VFC model. In the following experiments, the edge map was restricted to the range [0, 1] in order to remove the dependency on absolute image intensity value.

Such a new model can be used in medical CT image contour segmentation. The original CT image is shown in figure 1 (a), figure 1 (b) is the initialized contour. The GVF result, as shown in figure 1 (c), stop evolution at the wrong position, usually is called edge leak. Figure 1 (d) shows the results obtained using our proposed model. From this example we can see that the detection result of the GVF snake departs from the true boundary by the influence of false edge. But the improved model nearly converges to the true boundary.

![Figure 1](image1.png)

(a) The original medical CT image (b) the initialized contour (c) convergence of the GVF model (d) convergence of the proposed model

Such a new model can be used in MR image for heart contour extraction, also achieved good results. The original MR image and Initialized contour is shown in figure 2 (a), figure 2 (b) is the convergence result of the VFC model, figure 2 (c) shows the results obtained using our proposed model. We can see the accuracy of convergence result of the new model.
Figure 2 (a) The original MR image and the initialized contour (b) convergence of the VFC model (c) convergence of the proposed model

This result shows that the improved active contour model has large capture range, are less computationally expensive. Additionally, the improved model can avoid the edge leak by implementing a kind of new stop mechanism of evolution, and the accuracy of the improved model was superior to the traditional active contour model in the medical image segmentation.

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