3-D Reconstruction of Medical Image Using Wavelet Transform and Snake Model

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Abstract—Medical image segmentation is an important step in 3-D reconstruction, and 3-D reconstruction from medical images is an important application of computer graphics and biomedicine image processing. An improved image segmentation method which is suitable for 3-D reconstruction is presented in this paper. A 3-D reconstruction algorithm is used to reconstruct the 3-D model from medical images. Rough edge is obtained by multi-scale wavelet transform at first. With the rough edge, improved gradient vector flow snake model is used and the object contour in the image is found. In the experiments, we reconstruct 3-D models of kidney, liver and brain putamen. The performances of the experiments indicate that the new algorithm can produce accurate 3-D reconstruction.

Index Terms—medical image processing, 3-D reconstruction, wavelet transform, active contour

I. INTRODUCTION

Image segmentation is an important step in 3-D reconstruction. 3-D reconstruction of medical images is a hot subject in computer graphics and biomedicine image processing. It relates to image processing, computer graphics and some relational medical knowledge [1]. Research on 3-D reconstruction of medical images has significance in both science and practical application. 3-D reconstruction of medical images is broadly used in medicine diagnostic, virtual surgery system, plastic and artificial limb surgery, radiotherapy planning, and teaching of anatomy [2]. 3-D reconstruction technology includes surface rendering and volume rendering. Surface rendering has two categories. One is based on polygons and the other is based on voxels [3]. When the resolution of the images is high, volume rendering and voxels reconstruction algorithm can produce better 3-d models. However, when the distance of two slices is long, we should use the reconstruction method based on contours and polygons.

Image segmentation is an important technology in the digital human body. Many researchers have made great efforts to develop image segmentation algorithms [4]. However, up to now there has not been any all-purpose algorithm to solve all image segmentation tasks. At present some manual work is used in image segmentation. We present an image segmentation method which is suitable for 3-D reconstruction. At first, rough edge is obtained using multi-scale wavelet transform. With the rough edge, gradient vector flow snake model is used and the object contour in the image is found. The contour line is composed of many nodes. These nodes can be connected to form many polygons. Two methods for 3-D surfaces reconstruction are described in this paper: shortest diagonal line method and adjacent contours synchronous marching algorithm. We combine these two algorithms and propose a new 3-D surfaces reconstruction algorithm. Kidney, liver and brain are important apparatus of human body. In the experiments, we reconstruct 3-D models of kidney, liver and brain putamen, and these experiments demonstrate our algorithm.

II. MEDICAL IMAGE SEGMENTATION

A. Active contours

Active contours have been widely studied and applied in image analysis. Active contours have been first presented in 1987 by Kass [5]. A snake model can represent consecutive and closed object contours. The contour is composed of many nodes. The space between two nodes can be set and adjusted discretionarily. Because of these characteristics of the snake model, this image segmentation method is suited for 3-D reconstruction. The object boundary is represented as a parameter curve or surface generally. An energy function is associated with the curve, so the problem of finding an object boundary is categorized as an energy minimization process. However, there are several difficulties with traditional snakes. First, the initial contour must be close to the true boundary. Second problem is that it cannot capture boundary concavities of the image. Some methods have been proposed to improve the snake’s performance.

External forces have been applied to expand and shrink the active contour by Cohen [6], but it is not easy to ensure the force. Williams and Shah presented fast greedy algorithm to carry out the snake model and this method reduced the time cost. Eviatar and Somorjai presented an algorithm to solve the problem about the boundary concavities [7], but the initialization of original snake need manual work. Xu and Prince have proposed a new deformable model called gradient vector flow (GVF) snake [8], [9]. Instead of using image gradients as the
A snake presented by Kass is an elastic curve [5]. A final solution is given by the minimum total energy of the snake, which is the result of the equation

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

(1)

where \( \alpha \) and \( \beta \) are weighting parameters that control the snake’s tension and rigidity respectively, \( X'(s) \) and \( X''(s) \) denote the first and second derivatives of \( X(s) \) with respect to \( s \). The external energy function \( E_{\text{ext}} \) 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 \( I(x, y) \) which viewed as a function of continuous position variables \( (x, y) \), typical external energies designed to lead an active contour toward step edges are [2]

\[ E_{\text{ext}}^1(x, y) = -\left| \nabla I(x, y) \right|^2 \]

(2)

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

(3)

where \( G_\sigma(x, y) \) is a two-dimensional Gaussian function with standard deviation \( \sigma \) and \( \nabla \) is the gradient operator.

A snake that minimizes \( E \) must satisfy the Euler equation

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

(4)

To find a solution to (4), 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 hand side of (4) as follows

$$X_t(s, t) = \alpha (X - \beta X''(s, t)) - \nabla E_{eq}$$  \hspace{1cm} (5)

When the solution $X(s, t)$ stabilizes, the term $X_t(s, t)$ vanishes and we achieve a solution of (4). This dynamic equation can also be viewed as a gradient descent algorithm designed to solve (1). A solution to (5) can be found by discretizing the equation and solving the discrete system iteratively.

Although the traditional snake has found many applications, it is intrinsically weak in two main aspects: First, the initial border must be fairly close to the true boundary. Second active contours do not necessarily converge to boundary concavities. An example of traditional snake applied to a human slice image is shown in Fig.1. Fig.1 (a) shows a human slice image. Fig.1 (b) shows the initial border ($\alpha = 0.6$, $\beta = 0.0$). Fig.1(c) shows the border output of snake. And Fig.1 (d) shows the border output of GVF snake. Because the initial border is far from the true boundary, the active contours can not converge to the true boundary. Clearly, the capture range of traditional snake is very small.

Xu and Prince have proposed a new GVF snake to achieve better object segmentation [8], [9]. The GVF snake model remedied both of the shortcomings of the traditional snake. The basic idea of the GVF snake is to extend influence range of image force to a larger area by generating a GVF field. The GVF field is computed from the image. In detail, a GVF field is defined as a vector field $V(x, y) = (u(x, y), v(x, y))$ that minimizes the energy function

$$E = \int \left[ \mu (u_x^2 + u_y^2 + v_x^2 + v_y^2) + |\nabla f|^2 |V - \nabla f|^2 \right] dx dy$$  \hspace{1cm} (6)

where $f$ is the edge map which is derived by using an edge detector on the original image convoluted with a Gaussian kernel, and $\mu$ is a regularization parameter. Using the calculus of variations, the GVF field can be obtained by solving the following Euler-Lagrange equations

$$\mu \nabla^2 u - (u - f_x)(f_x^2 + f_y^2) = 0$$  \hspace{1cm} (7)

$$\mu \nabla^2 v - (v - f_y)(f_x^2 + f_y^2) = 0$$  \hspace{1cm} (8)

where $\nabla^2$ is the Laplacian operator.

Fig.1 (d) shows the result of GVF snake applied to Fig.1 (a). In our experiments, we used $\alpha = 0.6$, $\beta = 0.0$, and $\mu = 0.1$ for all GVF. The snakes were dynamically reparameterized to maintain contour point separation to within 0.5–1.5 pixels. In this example of GVF snake, the initial border is the same as that in Fig.1 (b). Comparing the result in Fig.1 (d) to the traditional snake result in Fig.1 (c), we can see that most of the active contours converge to the true boundary. The GVF snake has a much larger capture range than traditional snake. But the GVF snake cannot capture right object contours in some medical image. As shown in Fig.2, because of the influence of the image noise, this snake also fails to converge to the true boundary. To deal with these problems, we have developed an improved GVF snake. This new method is presented in detail in the following section.

B. Wavelet Analysis

A multi-scale edge detection method based on wavelet transform has been proposed by Mallat [10]. For two dimensional images, the wavelet transform at scale $a$ contains two components, $W_c$ and $W_d$, obtained by convolving the image $f(x, y)$ with the wavelets $\psi_c(x, y)$ and $\psi_d(x, y)$, respectively

$$W_c f(x, y) = f(x, y) * \psi_c(x, y)$$  \hspace{1cm} (9)

Figure 2. (a) medical image slice (b) convergence using a GVF snake
\[ W_{a} f(x, y) = f(x, y) * \psi_{a} (x, y) \] (10)

The wavelets \( \psi_{a} (x, y) \) and \( \psi_{a} (x, y) \) are dilations of a mother wavelet which approximates the first derivative of the Gaussian smoothing function \( \theta(x, y) \) at scale \( a \).

The two components of the wavelet transform, \( W_{a} \psi_{a} \) and \( W_{a} \psi_{a} \), represent the gradient vector of the image \( f(x, y) \) at scale \( a \). The modulus of the gradient vector is defined as

\[ M_{a} f(x, y) = \sqrt{W_{a} f(x, y)^2 + W_{a} f(x, y)^2} \] (11)

And the orientation of the gradient vector, \( A_{a} f(x, y) \) is given by

\[ A_{a} f(x, y) = \alpha(x, y) \quad W_{a} f(x, y) \geq 0 \] (12)

\[ A_{a} f(x, y) = \pi - \alpha(x, y) \quad W_{a} f(x, y) < 0 \] (13)

where

\[ \alpha(x, y) = \tan^{-1}(W_{a} f(x, y)/W_{a} f(x, y)) \] (14)

Fig.3 shows the edge detection result by a method based on wavelet analysis. Fig.3 (a) shows the corresponding orientation image. Fig.3 (b) shows the modulus image and Fig.3 (c) shows the edge image. Fig.3 (d) shows the boundary detection result by the improved GVF Snake model. In the experiments, the threshold used to calculate the modulus is 20. The choice of wavelet basis and the largest scale is based on the characteristics of the target image. For example, we chose the largest scale 3, and the Mexican hat function as the wavelet basis. From Fig.3 (d) we can see that the position of the edge point is clearer. Through this method, the GVF Snake can obtain accurate boundary.

Figure 3. (a) orientation image (b) modulus image (c) edge image (d) convergence using an improved GVF snake
III. 3-D RECONSTRUCTION

A. Reconstruction Algorithm

3-D reconstruction of medical images is a hot subject in computer graphics and biomedicine image processing. The primary purpose of 3-D surfaces reconstruction is to build a geometrical model of the body organ surfaces which are composed of many triangles. Important algorithms include biggest volume algorithm [11], shortest diagonal line algorithm [12], COOK algorithm [13], and adjacent contours synchronous marching algorithm [14], and so on.

We propose a new simple 3-D surfaces reconstruction method. This algorithm integrates the check result of the improved GVF Snake model, then extracts the shortest diagonal line and adjacent contours using the synchronous marching algorithm. Following is the primary ideas of the algorithm.

First, every node is connected to the nearest node at adjacent layer. In Fig.4 P1Q1 and P2Q2 are two lines of this type. Second, when two nodes at the upper layer and two nodes at the lower layer will be connected to form two triangles, the diagonal line must be shortest one. In Fig.4 the shortest diagonal line is P2Q1, and two triangles P1P2Q1, P2Q2Q1 are formed.

The number of contour nodes at adjacent layers may be unequal. So we propose a principle for adjacent contours synchronous marching. Take the case of Fig. 5, P1Q1 are the initial nodes of two adjacent contours respectively. After one marching step, node of contour one is P2, and node of contour two is Q2. Because P2 and Q2 are connected, we consider P1P2Q1Q2 as a tetrahedron, then the shortest diagonal line P2Q1 is selected. We get two triangles P1P2Q1 and P2Q2Q1. Marching one step again, the node of contour one is P3, the node of contour two is Q3. But P3 is not connected with Q3. Actually P3 is connected with Q5, P2 is connected with Q3. We can check that the marching speed of contour two is slower. Under this condition we connect triangle P2Q3Q2. For the same reason, triangle P2Q4Q3 is formed at the next step. When node Q4 at contour two moves to Q5, the speed at P2P3 and Q4Q5 are synchronous. Here we select the shortest triangle Q4P3 and form two triangles P2P3Q4, Q4P3Q5.

B. Experiments

An experiment on reconstructing a 3-D surface of the kidney is shown in Fig.6. The performance indicates that our new algorithm can produce accurate reconstruction. The original images are from an image database. There are 1878 images in the whole body images, and the number of kidney images is 105.

To segment the images and get the contours of the kidney, we approach the object boundary using original GVF Snake model at first. Some kidney area is disturbed by noise and cannot be distinguished by the original GVF Snake. Then we use improved active contour model based on wavelet transform presented in this paper. At the top and bottom of the kidney, the structure of the

![Figure 4. diagonal line](image1)

![Figure 5. sketch map of triangle](image2)
images is simple. The GVF snake model only can obtain good contour nodes. But at the middle part of the kidney, because of the increase of noise and the complexity of kidney structure, GVF snake cannot get accurate contour nodes like those in Fig. 2 (b). Here, the improved GVF snake algorithm described in this paper is used and accurate contour nodes are obtained. The data of every contour node is saved and is read by our 3-D reconstruction program module.

After obtaining the data of the contour node coordinate, we build the 3-D model by simple three-dimensional reconstruction designed in this paper. To get better visualization effect, we set appropriate lamp-house and coordinate system. And much more true and lubricous kidney surface is obtained. The new image segmentation arithmetic and 3-D reconstruction can avoid the misplay and eliminate the error using manual method. Finally, through triangle connected algorithm presented in this paper, we can see the 3-D surfaces reconstruction result in Fig.6. Our 3-D reconstruction software system is based on OpenGL, and the reconstruction figure can be shown through arbitrary angle.

Using the method of this paper, we segment the images in the liver and the brain putamen as shown in Figure7, Figure 9. Then the 3-D surfaces reconstruction model is obtained as shown in Figure 8, Figure 10, and the result is preferable.

IV. CONCLUSIONS

3-D reconstruction of medical images is a hot subject in computer graphics and biomedicine image processing.
Image segmentation is an important step in 3-D reconstruction. In this paper, we have presented a new image segmentation algorithm combining gradient vector flow snake and wavelet analysis. At first, we get the edge map image using a multi-scale algorithm based on wavelet analysis. With the edge map, gradient vector flow Snake can capture the accurate object boundaries. Our method solves the problem that edges detected using the wavelets method is not consecutive. The ability of the snake model to withstand noise is improved. A simple 3-D reconstruction algorithm is used to construct the 3-D model of medical images. Kidney, liver and brain are important apparatus of human body. In the experiments, we reconstruct 3-D models of kidney, liver and brain putamen. The performance of experiment indicates that the new algorithm can produce accurate 3-D reconstruction.

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