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Contour Extraction in Medical Images Using B-Snake Model

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ABSTRACT

In this paper, a close-form B-snake model is presented for contour extraction in medical images. Based on our previous research work [10], the Principal Component Analysis (PCA) has been applied to our B-snake model, in order to use available statistical information about the desired object shape. This approach allows the deformation of B-snake to synthesize the shape similar to those in the training set. Experimental results show the robustness and accurateness of proposed model in object contour extraction in medical images.

1. INTRODUCTION

Contour extraction is a very important procedure in medical image process. Many medial image analysis applications, like the measurement of anatomical structures, require prior extraction of the organ from the surrounding tissue. Our special interest is the extraction of the ventricle from magnetic resonance images (MR) for the case where the priori knowledge is available.

Snake, or active contour was originally developed by M. Kass [1]. It was deformed by the external and the internal forces. B-snake, which is using a parametric B-spline representation of the curve to replace original point-based snake. It greatly reduces the number of parameters to control and the smoothness requirement has been implicitly built into the model.

In this paper, we are combined B-snake with a statistical model for getting a better extraction result. The structure of this paper is arranged as follows. In Section 2, a review of the existing B-snake model and statistical model is presented. Section 3 briefly introduces a B-snake model. In Section 4, the statistic model is given to guide the B-snake deformation. The simulation results are shown in Section 5. This paper concludes in Section 6.

2. RELATED WORKS

Cootes presented a point distribution model [2] for building flexible shape models. The shape is represented by a set of labeled points. The shapes are aligned and the deviations from the mean are analyzed using principal component analysis. Unfortunately, the labeled points have to be chosen manually for each shape in the training set, it is very time consuming. Moreover, as the method works by modeling how different labeled points tend to move together as the shape varies, if the labeling is incorrect, with a particular point placed at different sites on each training shape, the method will fail to capture shape variability.

As an extension research work to the point distribution model, Baumberg proposed a cubic B-spline model [3] for detecting and tracking the walking pedestrians. The control points of B-spline are treated exactly the same way as the labeled points of point distribution model [2]. This method has been applied to a real-time processing system.

Stammberger [4] proposed a B-spline snake algorithm for the segmentation of the knee joint cartilage from MR images by using a multi-resolution approach. As the external forces are generated by image edges and the distance transformation of a standard model, the B-snake may not deform to a desired object, because there is no statistical information has been included in this algorithm.

Mário presented an approach to unsupervised contour representations and estimations by using B-spline [5]. The problem is formulated in a statistical framework with the likelihood function being derived from a region-based image model. However, no any priori knowledge of the shape is used in this model.

Wang [6][7][8] presented a B-snake based lane model for lane detection. The external forces in this model are designed based on the perspective relationship of lane boundaries on the image plane. However, although the results are good in lane detection, the number of control points is fixed to three, this limits the capability to describe the complex shape. In their later paper [10], a structure-adaptive B-snake model with a strategy of adaptive control point insertion was proposed for segmenting the complex structures in medical images.

Here, we present a B-snake model using statistical information, it is an extension of our previous research work [10]. The details are given in the followings.

3. B-SPLINE SNAKE

3.1. A Close Cubic B-Snake Model

A close cubic B-spline has $n+1$ control points $\{Q_i = [x_i \quad y_i]^T, i = 0,1,\ldots,n\}$, and $n+1$ connected curve segments $\{g_i(s) = (u_i(s), v_i(s)), i = 1,2,\ldots,n+1\}$. Each curve segment is a linear combination of four cubic polynomials by the parameter s, where s is normalized between 0 and 1 $(0 \le s \le 1)$. That is,

$$g_i(s) = M_R(s)\begin{bmatrix} Q_{(i-1)\bmod(n+1)} \\ Q_{i\bmod(n+1)} \\ Q_{(i+1)\bmod(n+1)} \\ Q_{(i+2)\bmod(n+1)} \end{bmatrix}, \quad i = 1,2,\cdots,n+1 \qquad (1)$$

where

$$M_R(s) = \begin{bmatrix} s^3 & s^2 & s & 1 \end{bmatrix}\begin{bmatrix} -\frac{1}{6} & \frac{1}{2} & -\frac{1}{2} & \frac{1}{6} \\ \frac{1}{2} & -1 & \frac{1}{2} & 0 \\ -\frac{1}{2} & 0 & \frac{1}{2} & 0 \\ \frac{1}{6} & \frac{2}{3} & \frac{1}{6} & 0 \end{bmatrix}. \qquad (2)$$

A B-snake is defined as follows:

$$r(s) = \sum_i g_i(s), \text{ where } 0 \le s \le 1. \qquad (3)$$

The external energy term on $r(s)$ is defined as $E(r(s))$. Therefore, the total energy function of the B-snake $E_{B-snake}$ can be defined by integrating $E(r(s))$ along the B-snake. That is,

$$E_{B-snake} = \int_0^1 E(r(s))ds. \qquad (4)$$

However, as we found that, the projection of $E(r(s))$ in the tangent axis of each sampled point in B-snake, did not help to deform the B-snake to desired boundary and just increased the distance between the sampled points on the B-spline curve. Hence, in order to speed up approach, external force $E(r(s))$ in equation (4) is replaced by $\hat{E}(r(s))$, the projection of $E(r(s))$ at the normal axis of that point on B-spline curve. $E(r(s))$ and $\hat{E}(r(s))$ are shown in Figure 1.

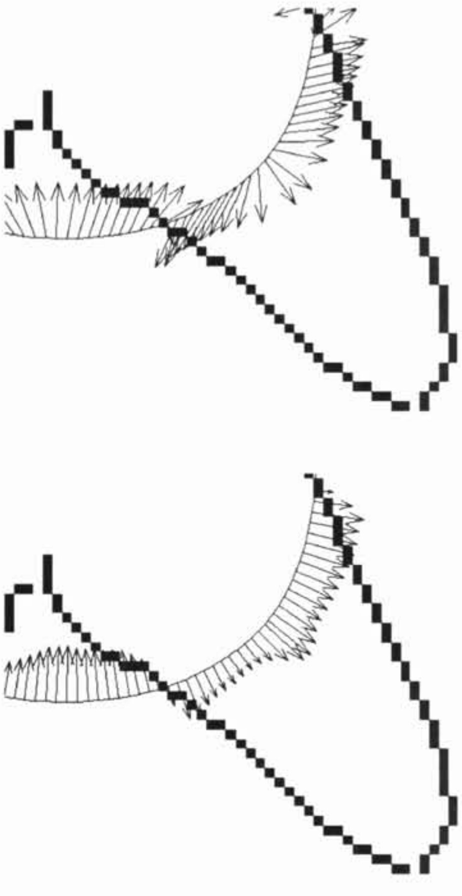

Figure 1 The difference between $E(r(s))$ and $\hat{E}(r(s))$

3.2. Estimating B-Snake Parameters by Image Data

Based on the initial location of the control points, the Minimum Mean Square Energy Approach (MMSE) with an adaptive strategy of inserting control points is used to deform B-snake to the studied object. For more details, please refer to our paper [10].

Figure 2(a) shows a result of using B-snake for ventricle extraction from MR image.

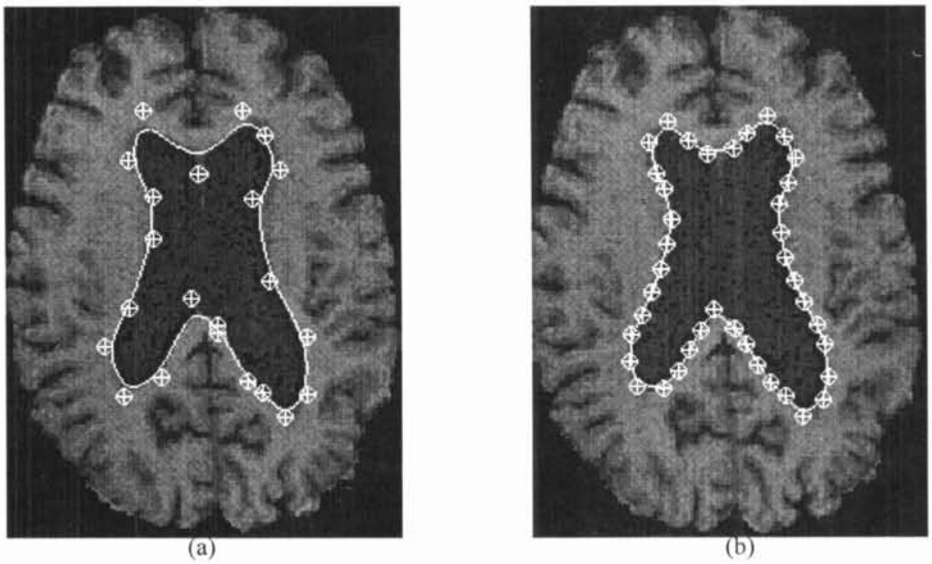

Figure 2 B-snake using (a) 22 control points and (b) 40 control points.

4. B-SNAKE APPROACH USING PRINCIPAL COMPONENT ANALYSIS

Principal Component Analysis (PCA) is a classical statistical method [13]. This linear transform has been widely used in data analysis and processing. We have implemented PCA to B-snake as an effect approach to the data.

In order to use statistical information to guide the B-snake deformation, the correspondence problem between two shapes should be solved. First we have to reconstruct B-snake with a fix number of control points, and then find the corresponding control point between the training sets.

4.1. B-spline Re-Construction

B-spline can be easy re-constructed with a fix number of control point based on a fix ratio of whole length for each segment on spline curve. The method we are using here can be found in [11]. Please see Figure 2(b) for an example of 40 control points of B-snake, it is re-constructed from Figure 2(a) which has 22 control points.

4.2. Shape Alignment Strategy

The method used here for determining the correspondence between B-snakes is obtained from the paper [9]. It is a shape alignment algorithm which is using an affine-invariant feature. A set of feature points of piecewise deformable model are extracted directly from the sample points, which are evenly distributed along the given shape. For each feature point, an attribute vector, which is calculated by the areas formed by adjacent feature points, has been assigned to it. As the attribute vectors are affine-invariant, shape alignment could be achieved by an error minimization process.

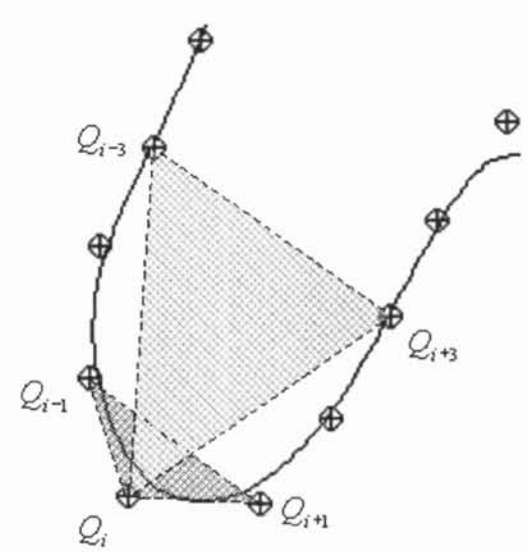

Figure 3 Schematic representation of the concept of the "attribute vector" on the *i*th control point. The area of a triangle $Q_{[i-vs]}Q_{[i]}Q_{[i+vs]}$ is used as the *vs*th element of the *i*th attribute vector F_i. Here, $1 \le vs \le n/2$.

For our case, B-snake, these feature points can be simply replaced by the control points of B-snake, as we know B-spline is affine-invariant. The attribute vector for the ith control point, F_i, is generated by adjacent control points. Please see the shadow areas in Figure 3.

4.3. Modeling the Shape Distribution from the Training Set Using PCA

Given a set of the training data of aligned control points of B-snake, $\{Q_T\}$, the approach is as follows:

1. Compute the mean of data, $\overline{Q}_T$ and the covariance of the data, C.
2. Compute the eigenvectors, ϕ_i and corresponding eigenvalues λ_i of C, and sort ϕ_i by the size of their corresponding eigenvalues.
3. Let Φ contains the m eigenvectors corresponding to largest eigenvalues, then use below formulas for fitting the control point vector Q' of the model to the control point vector Q of the aligned B-snake shape:

$$Q' = \overline{Q}_T + \Phi H \tag{5}$$

where H is a m dimensional vector given by

$$H = \Phi^T\left(Q - \overline{Q}_T\right) \tag{6}$$

Once obtaining the best control point vector Q', we transform Q' back to update the positions of control points in the current B-snake by using the affine-transformation matrix A^{align}. For more details on how to get A^{align}, see [12].

4.4. Complete Algorithm

The complete algorithm using both affine invariant alignment and statistical information is as follows:

1. Get a reference model $\{Q_i^{model}, i = 0,1,\ldots,N\}$. It can be done by the method presented in Section 3.
2. Initialize the B-snake as $\{Q_i^{model}, i = 0,1,\ldots,N\}$.
3. Deform the B-snake by using MMSE to minimize external force (Section 3.2). If the iteration number exceeds a predefined number or external force among B-snake is below a define value, go to step 6.
4. Align the current snake configuration with the standard model contour by using the affine-transformation matrix A^{align} calculated from the snake to the model [9]. Then, stack the aligned snake as a point vector

$$Q = \left[x_0^{align}, y_0^{align}, \ldots, x_N^{align}, y_N^{align}\right]^T$$

5. Map the control point vector into the new vector Q into the new vector Q' using the statistical model, $Q' = \overline{Q}_T + \Phi H$, which is described in Section 4.3. Then, transform Q' back into the original coordinate space of the snake via the inverse matrix of A^{align} and update the B-snake. Go to step 3.
6. Stop.

5. EXPERIMENTAL RESULTS

We have simulated the above algorithm by using Matlab codes and tested to real MR medical images.

There are more than 50 shapes with 40 control points have been involved to form the training sets Some results of our B-snake model are shown in Figure 4. The grays are the initial shapes of B-snake in each image, while the bright are the final results. These results show that our B-snake model approaches to the desired object precisely.

6. CONCLUSION

We have presented a B-spline snake model using statistical information for extracting 2D complex shapes from the medical images. The obtained results have showed that this model can be used to achieve a more accurate segmentation and hence a refined model.

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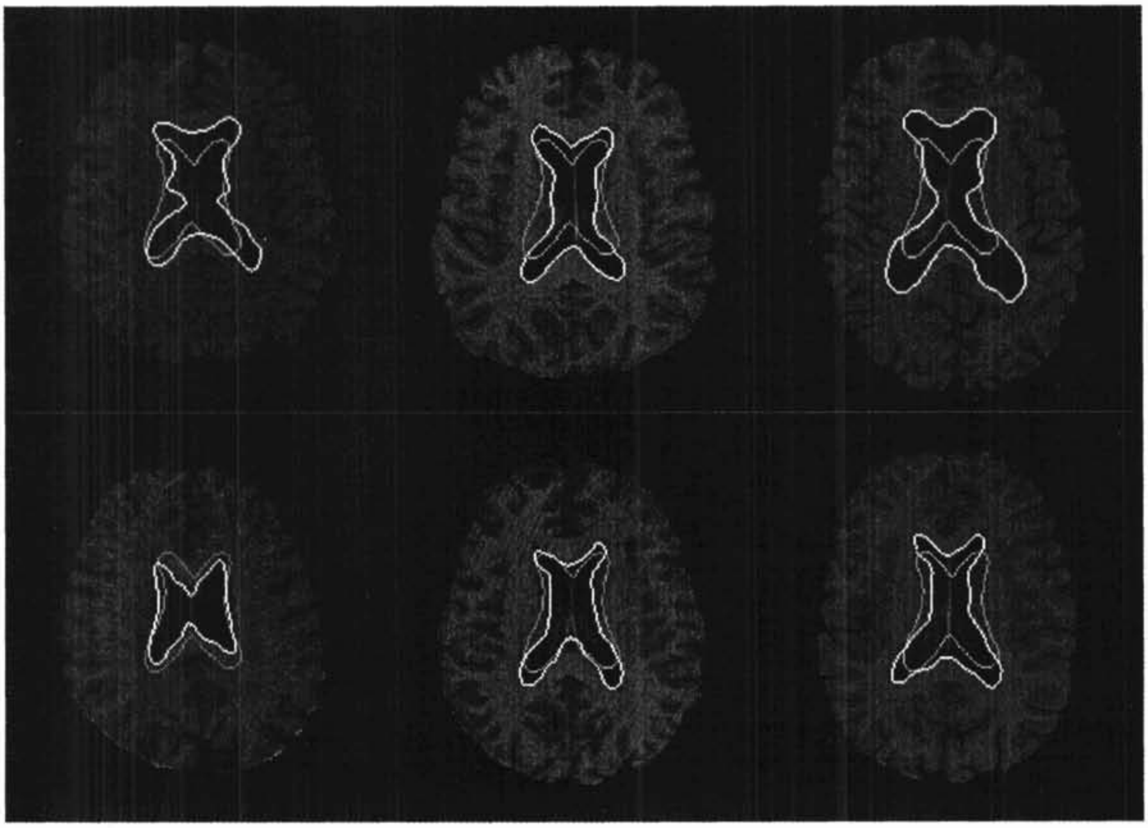

Figure 4 Some segmentation results of MR brain images using B-snake model