

A method for brain 3D surface reconstruction from MR images*

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Due to the encephalic tissues are highly irregular, three-dimensional (3D) modeling of brain always leads to complicated computing. In this paper, we explore an efficient method for brain surface reconstruction from magnetic resonance (MR) images of head, which is helpful to surgery planning and tumor localization. A heuristic algorithm is proposed for surface triangle mesh generation with preserved features, and the diagonal length is regarded as the heuristic information to optimize the shape of triangle. The experimental results show that our approach not only reduces the computational complexity, but also completes 3D visualization with good quality.

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The three-dimensional (3D) reconstruction of brain structures from magnetic resonance (MR) images is a crucial work in clinical diagnosis, surgical planning and the analysis of neuroanatomical variability. From a set of parallel slices generated from MR image, it is possible to reconstruct and display the external surface of the organ by using the triangle meshes of the geometric modeling. Irregular triangle meshes have become more and more popular, and are frequently used in many different areas, such as computer graphics, 3D modeling, computer games and movie production. Many algorithms for solving the triangulation problem have been proposed^[1,2]. A well-known grid-based method is marching cubes^[3,4], which is the isosurface extraction generated on local criteria. Delaunay triangulation is another widely used algorithm in computational geometry^[5,6]. Recently, some researchers try to use vector machine based method^[7], which transforms an original 3D object space into a high dimensional feature space, and it shows better result than the cube based methods, but its accuracy depends on the training data set processing. The general cube based method of these triangle meshes is to find a polyhedral surface from a set of vertices arbitrarily distributed in space, which is complicated. However, if the problem is limited to reconstructing a surface from tomographic slices, such as the sequence MR images, the particular structure of such data will greatly reduce the complexity of reconstruction, because the vertices dataset consists of the set of contour points of all slices.

In this paper, triangle meshes are applied to construct 3D model, since their conceptual simplicity allows more

flexible and highly efficient processing. We design a method which allows automatical 3D triangle mesh generation for MR slices by applying heuristic information as local decision criterion. The external surface is approximated by linking each set of contours from two consecutive slices with triangular patches, thus forming the 3D approximation, and the consequent use of triangle meshes as surface representation avoids error-prone conversions. This idea is similar to finite element analysis^[8], in which the construction model is typically derived from the extraction of triangular surface meshes and these meshes should satisfy the requirements of triangle quality and accuracy.

The mesh surface should cover a specified domain. The size of triangles should be neither smaller than necessary nor larger than desired, and the angles of triangles should be proper.

A triangle surface S consists of a geometric component and a topological component:

$$S = \{\varepsilon, \mathbf{v}\}, \quad (1)$$

where the topological component is represented by a set of vertices

$$\mathbf{v} = \{v_1, v_2, \dots, v_n\}, \quad (2)$$

and the geometric component specifies the connectivity of the meshes in terms of the edges of the respective graph,

$$\varepsilon = \{e_1, e_2, \dots, e_E\}, \quad e_i = \mathbf{v} \times \mathbf{v}. \quad (3)$$

Each vertex v_i has its 3D coordinates of $(x_i, y_i, z_i) \in \mathbf{R}^3$.

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To construct 3D model based on the MR image tomographic slices, it is crucial to obtain the object's contours. We use the image segmentation method to divide the meaningful region, such as the head and brain organizations. Medical image segmentation is a challenging task in many medical applications, such as surgical planning and abnormality detection. There are lots of methods for automatic and semi-automatic image segmentation, and here we use the gradient vector flow (GVF) snake algorithm proposed by Xu et al^[9] to obtain the brain contours extracted from the de-noised MR images.

In the GVF snake algorithm, external force is defined by a concept of GVF as $v(x,y)=(u(x,y), v(x,y))$. The solution of the GVF deformable models can be found by the iteration equation:

$$X_i(s,t) = \alpha X''(s,t) - \beta X''''(s,t) + V, \quad (4)$$

where $X(s,t)=(x(s,t), y(s,t))$ represents the deformable models, and V can be obtained by minimizing the energy equation:

$$\varepsilon = \iint [\mu(u_x^2 + u_y^2 + v_x^2 + v_y^2) + |\nabla f|^2 |V - \nabla f|^2] dx dy. \quad (5)$$

We program the edge detecting method to get the data of each contour. Put the contours in sequence as the order of tomographic slice number, which can be assigned as the z-axis. Then, the adjustable step sampling is applied to each contour to get the node that can be processed in triangle meshes. We save the data and put them into a 3D data set for the next mesh generation.

Triangle mesh is practically constrained by some feature nodes. We divide these feature nodes into two types, which are the characteristic points located in severe curvature places and the constraint points corresponding to the electrode position.

The characteristic points represent the MR image contour feature of each slice, such as the nose tip on one's face. If the node is selected in accordance with a fixed span, it will lose some feature points which contain the characteristics of model information. Suppose y_{i-1}, y_i and y_{i+1} are any three adjacent points in contour z , the feature points y_i can be found through computing the slope of neighboring points which satisfy the formula of $K_{i,i-1} \times K_{i,i+1} < 0$, where $K_{i,i-1}$ and $K_{i,i+1}$ are the slopes of lines $y_i y_{i-1}$ and $y_i y_{i+1}$.

Another type of feature nodes is the constraint points which are related to image registration. The individual head and brain morphology obtained by MR image is not only an essential aspect of the functional localization of brain activity based on multi-channel electroencephalography (EEG), but also is an important issue electrocorticographic (ECoG) research^[10]. In order to be able to use the EEG (or ECoG) with high spatial resolution for accurate brain function mapping and neurophysiology studies, the exact location of the electrodes on the head (or brain) surface should be known.

There are many matching techniques with different accuracies for the registration of EEG (or ECoG) and MR

image data. These approaches make the transformation of electrode positions and MR image data into a single coordinate system, which allow a more realistic head model for the reconstruction of electric sources and the localization and validation results in relation to morphological structures. We do not discuss these methods in this paper, since we only use the matching results as the constraint nodes for triangle mesh.

From above, the feature nodes can be achieved and saved in the data set as a part of the sampling nodes. Then the sampling of the contour points is based on an adaptive step which can be adjusted by the surface curvature. Vertex density has to be locally adapted to the surface curvature, i.e., the flat areas are sparsely sampled, while the sampling density in detailed regions is sufficiently higher. Taylor expansion reveals that the approximation error is of the order $O(h^2)$, where h denotes the maximum edge length. Hence, the approximation error of a triangle mesh is inversely proportional to the number of its patches.

Now, our problem is to reconstruct a surface from MR tomographic slices. This surface structure of the data can be exploited by a heuristic strategy, and we call it as short diagonal method which is developed based on the principle proposed in Ref.[11]. The heuristic information constrains the shape of the patch similar to equilateral triangle, which can deduce the approximation error in the process of reconstruction for MR image. The schematic diagram of short diagonal method is shown in Fig.1.

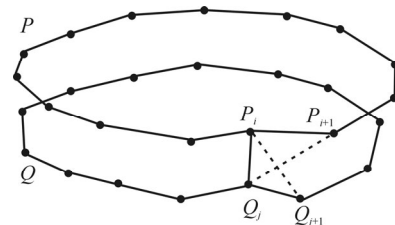


Fig.1 The schematic diagram of short diagonal method

Let z_1, z_2, \dots, z_k be the sequence of ordered contour section levels. We consider the contour Q at level z_{k-1} and the contour P at the adjacent level z_k . Suppose P_i with $1 \leq i \leq M$ is the sequence of points defining contour P , and Q_j with $1 \leq j \leq N$ is the sequence of points defining contour Q , which are ordered in a counterclockwise direction. The mesh of triangular patches linking P and Q can be achieved by using the short diagonal rule. Suppose P_i is any point in P , and then Q_j is the point in Q which has the shortest length to P_i . Other sampling nodes, such as P_{i+1} and Q_{j+1} , are obtained by dividing P and Q by the length of $L(P_i Q_j)$. If the diagonal lengths satisfy that $L(P_i Q_{j+1}) < L(P_{i+1} Q_j)$, connect P_i with Q_{j+1} , so the triangle is $Q_j P_i Q_{j+1}$. Otherwise, connect P_{i+1} with Q_j , and then the triangle is $Q_j P_i P_{i+1}$.

According to the short diagonal rule, once the first node is set on one contour, the other first nodes on neighbor contours are fixed. These first nodes of adjacent contours are formed to a line, which we call as the baseline of the first triangle. In the process of sampling, the saved

feature points should be sampled as mesh nodes to ensure the curvature characteristics and the constraint points are preserved. The 3D surface reconstruction is processed by meshing a series of image contours for the corresponding spatial geometry structure. The algorithm for triangle mesh with preserved feature can be decomposed into three steps as follows. Firstly, initialize the uniformed contour slices to find the feature nodes. The characteristic points are achieved by computing the slope K , and the constraint points (electrode positions) are achieved by image registration method. Secondly, sampling from the data set $(x_i, y_i, z_i) \in \mathbf{R}^3$, set the contour sampling step (around a fixed step) according to the distance of adjacent feature points, and the sampling step may be several different values under the condition of more than two constrained points. Repeat the above process, and the mesh data matrix is achieved for each contour. Thirdly, use the short diagonal method to complete the 3D triangle mesh. A global link between contours is performed by linking each node of the contour z to the nearest node of the contour $z+1$. The diagonal length is as the heuristic information to the triangular mesh.

This algorithm offers mathematical guarantees that mesh constraints and feature nodes can be met. The resulting mesh is shaped very well, and Fig.2 shows the example for the adjacent four contours of brain slices. We can see the problem is limited to the triangulation problem between each pair of consecutive slices. 3D reconstruction surface is composed by piecewise linear surfaces, and the set of surface vertices consists of the set of contour points of each slice.

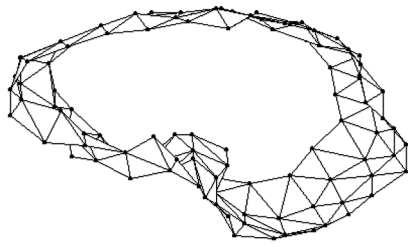


Fig.2 Mesh results for adjacent four contours of brain slices

We perform a series of experiments based on real MR images to evaluate the proposed 3D triangulation mesh model. We got the head MR images from Tianjin First Center Hospital in China, including 51 head tomography slices of one person, and only 21 slices are shown in Fig.3, where the image size of each slice is 128×128 . Using the GVF snake algorithm, the brain MR image slices are successfully segmented from the original head MR images, and 45 brain MR images are achieved. Fig.4 shows the brain slice sequence corresponding to Fig.3. The contours of each slice of head and brain are obtained through edge detecting, then we can have the 3D dataset for the next mesh by stacking these slices data in accordance with the sequence number. The visualizations of head and brain point cloud data are shown in Fig.5.

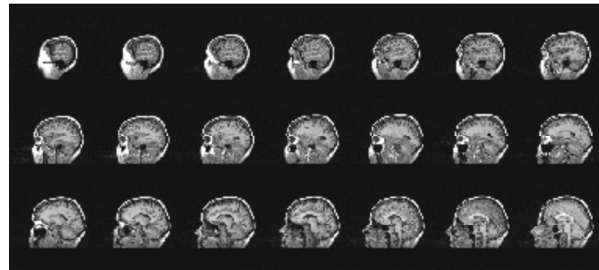


Fig.3 21 head MR slices got from hospital

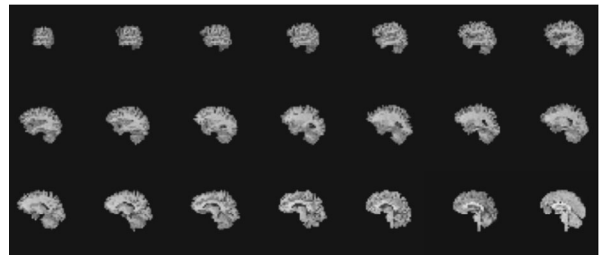


Fig.4 Brain slices extracted from the head MR image by the GVF snake algorithm

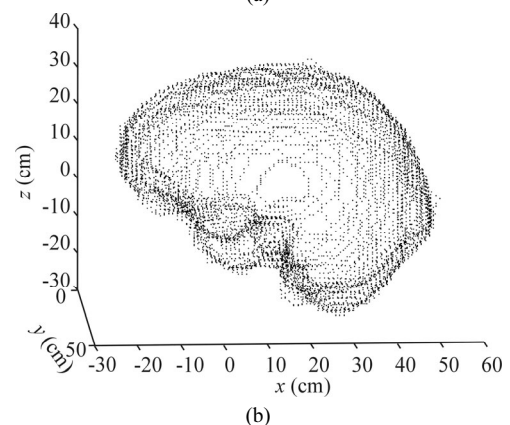
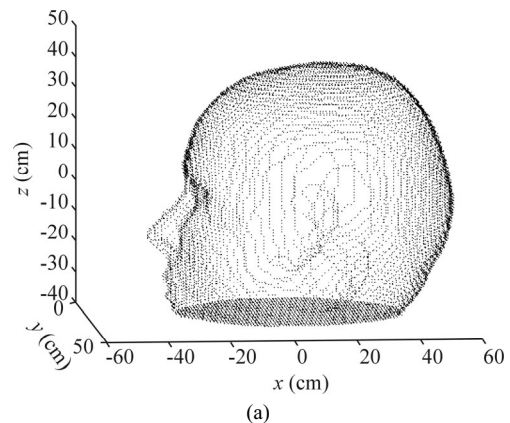


Fig.5 3D point cloud data of (a) head and (b) brain

Using the short diagonal method for generating mesh patches, we get 385 nodes and 766 triangular patches for the brain, and 402 nodes and 800 triangular patches for the head. The algorithm is heuristic with short diagonal, and feature points are ensured as vertices in the meshing process. The head reconstruction result with feature points is shown in Fig.6(a), and it can be seen that the

generated triangles are almost equilateral. The nodes in bold represent the feature points, and there are two types of feature points. The bold nodes near nose are the characteristic nodes located in severe curvature places, and those on the top are the constraint nodes corresponding to the electrode position. Fig.6(b) and (c) show the brain mesh result and the visualization of its 3D reconstruction. We can see that the mesh quality is high enough to build a satisfactory brain 3D model.

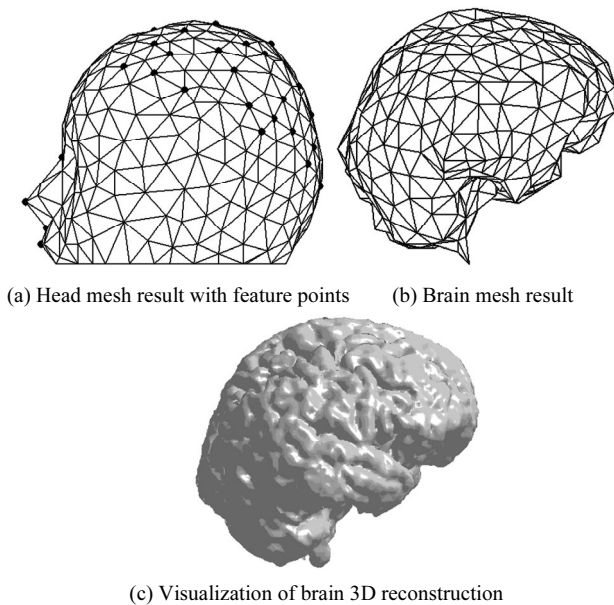


Fig.6 The mesh results and 3D visualization

There are many measures to evaluate the element quality^[12]. One commonly used mesh quality measure is using the ratio:

$$q = 2 \frac{r_{in}}{r_{out}} = \frac{(b+c-a)(c+a-b)(a+b-c)}{abc}, \quad (6)$$

where a , b and c are the edge lengths. $q=1$ means the equilateral triangle, and $q=0$ means the degenerate triangle (zero area). As a general rule, if all triangles have $q>0.5$, the results are good. The triangles produced by our algorithm tend to have exceptionally good element quality. The head mesh has $q>0.7$, and the brain mesh has $q>0.6$. These results are better than a typical Delaunay refinement mesh with Laplacian smoothing.

In Ref.[13], they make a comparison of several algorithms, which indicates that the traditional marching cube method takes 3 130.5 s on surface reconstruction, while our method spends an average of 926 s, which is just longer than the time of vector based approach (527 s).

Considering simplicity and efficiency evaluation, our approach is a good solution with acceptable time.

We show our method in detail to construct the brain 3D model from MR images. We propose a mesh algorithm for MR image 3D surface reconstruction with preserving feature points, and the diagonal length is regarded as the heuristic information to optimize the shape of triangle. The results demonstrate the mesh quality and effectiveness on the brain surface reconstruction. The mesh algorithm is much simpler than other algorithms because the process is simplified to the problem of linking adjacent contours of MR image. Moreover, our technique typically produces meshes with very high quality. On the execution time, the algorithm can be further optimized to improve efficiency, which will be the focus of our next work.

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